# MODELLING COMPRESSIVE STRENGTH OF CONCRETE FROM NON-DESTRUCTIVE TESTS USING MACHINE LEARNING

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In Partial Fulfillment of the Requirements for the Degree of

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With Specialization in Construction Technology and Management

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This thesis, entitled **MODELLING COMPRESSIVE STRENGTH OF CONCRETE FROM NON-DESTRUCTIVE TESTS USING MACHINE LEARNING**, prepared, and submitted by thesis group, composed of:

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In partial fulfillment of the requirements for the degree of **Bachelor of Science in Civil Engineering with Specialization in Construction Technology and Management (CIV-CTM)** has been examined and is recommended for acceptance and approval for **ORAL DEFENSE**.

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**MODELLING COMPRESSIVE STRENGTH OF CONCRETE FROM NON-DESTRUCTIVE TESTS USING MACHINE LEARNING**

prepared and submitted by **Villanueva, Daniel Kenneth** in partial fulfillment of the requirements for the degree of **Bachelor of Science in Civil Engineering with Specialization in Construction Technology and Management (CIV-CTM)** has been examined and is recommended for acceptance.

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## ABSTRACT

Concrete is that the most generally used structural material for construction these days. Traditionally, concrete has been created from a few well-defined components: Cement, water, fine aggregate, coarse aggregate, etc. In concrete mix design and quality control, the compressive strength of concrete is regarded as the most needed property.

The main objective is to model the compressive strength of concrete obtained from non-destructive test using machine learning. The specific objectives are to narrow down the search to factors that significantly contribute to the compressive strength of concrete, to compare results from destructive methods with non-destructive methods and to create a model using the factors to be considered.

Linear regression has successfully been used as a sanity check. The most successful non-NN algorithm, stepwise quadratic regression with interactions was also featured. The repeatability of the results is also a matter of interest since the neural network also changes rapidly even without changing the neural network parameters.

The neural network, when tweaked, was also able to give a performance better than the other methods. It was demonstrated that neural networks could give results better than other methods could.

Nevertheless, the investigation also made known that more data would be appreciated, especially outside of the 10-45MPa range.

A model for the compressive strength of concrete from non-destructive test using machine learning has been obtained. The model is a neural network that contains only the more influential variables. This model could be seen on subsection V.5.3.2 (page 166). This model (tweak neural network) is the best due to the higher R-squared compared to the other models. The best model contains twenty-one inputs with a hidden layer of size one to produce one output. This model has an R-squared of 0.9773.

More data is recommended to be gathered. The analysis could be augmented if there is more data.

More factors could be considered. The only non-destructive factor that was used in the analysis was rebound number and ultrasonic pulse velocity. Other factors such as

Leeb hardness, electrical resistivity, and point load index would still need a greater foray into the current research.

**Daniel Kenneth Villanueva**

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# Chapter I

# Problem Setting

## I.1 Background of the Study

### *I.1.1 Historical background*

Concrete is that the most generally used structural material for construction these days. Traditionally, concrete has been created from a few well-defined components: Cement, water, fine aggregate, coarse aggregate, etc. In concrete mix design and quality control, the compressive strength of concrete is regarded as the most needed property.

Many other attributes of concrete, such as elastic modulus, water tightness or impermeability, resistance to weathering agents, etc. are related to the strength. The compressive strength of concrete is many times higher than other types of strength, and most concrete elements are chosen to take advantage of the greater compressive strength of the material. Most frequently, the ultimate target in the mixture design is the 28th day compressive strength. The 28th day compressive strength is usually found based on a standard uniaxial compression test and is considered universally as a general index of concrete strength. The

compressive strength of concrete is associated to mix proportions and mix preparation techniques, but the outcome of the compression test of a specimen can be changed by the shape, dimension, and the boundary conditions of the specimen. Traditionally, concrete mix is designed considering previous experiences. However, data from previous experiences is restricted since all doable combinations of parts, proportions, and mixing techniques haven't been investigated or revealed. (J.-I. Kim et al., 2004)

Durability performance of concrete structures is sadly not perpetually pretty much as good as anticipated for a spread of reasons. The important drive for the various developments of non-destructive testing strategies and instrumentality has been the necessity of business worldwide for long-run maintenance ways. There are vital advances in instrumentality capabilities and a variety of latest techniques associated with sturdiness and integrity assessment. These techniques became established in follow. The troubleshooting and maintenance role of in place testing remains assured. However, attitudes amongst the engineering community towards in-place testing for internal control throughout construction stay mostly unchanged. this is

often except restricted acceptance of testing for strength development observance and increased use of covermeters. Cubes/cylinders stay the ‘gold standard’ for concrete acceptance for the predictable future. (Maierhofer et al., 2010)

In 1974, many high-alumina-cement pre-tensioned beams within the United Kingdom of Great Britain and Northern Ireland collapsed attributable to major loss of concrete strength because of the ‘conversion’ of the high-alumina-cement concrete underneath unfavorable environmental conditions. This led to a nationwide program of examination and assessment. (Maierhofer et al., 2010)

What is meant to be finished regards to non-destructive testing and compressive strength is to seem at the numerous factors that might influence the compressive strength of the concrete. The strategies for non-destructive testing embody the Rebound Hammer (RH) check and Ultrasonic Pulse Velocity (UPV) check.

Non-destructive testing could be a type of testing that preserves the integrity of the section being analyzed. this is often helpful since it permits for the concrete strength initially planned to be compared with the current concrete strength. this is often helpful since the strength of the concrete might not be as secure or would

have degraded over time because of environmental factors. (Maierhofer et al., 2010)

Non-destructive testing is a technique that permits the investigation of the properties of concrete without requiring for the concrete to be damaged.

Non-destructive testing is not much used in the Philippines. However, Dr. Ongpeng tested concrete beams using Portable Ultrasonic Non-destructive Digital Indicating Tester, known as PUNDIT. Testing has found that UPV result at the early age of concrete is not correlated with the 28 day compressive strength of concrete. (Ongpeng, 2015)

on-destructive testing conjointly incorporates a drawback with regards to the guideline calculations given by the manufacturer. The guideline equation for the employment of various non-destructive testing instruments have evidenced to be inadequate. this is often since the conditions of the concrete utilized in the business might be completely different from how the manufacturer have created the concretes used for testing.

Despite the key efforts in manufacturing British and European Standards, there are notable gaps, particularly with reference to reinforcement corrosion assessment. (Maierhofer et al., 2010)

A motivation for modelling the concrete strength comes from the very fact that there is a lot of inequality with regards to results from different literature. The figure below shows a part of the discrepancy.

The construct of modelling the compressive strength comes from the utopic vision that if all the factors are thought about, then it might be doable to slim down the causes for the discrepancies in the curves.

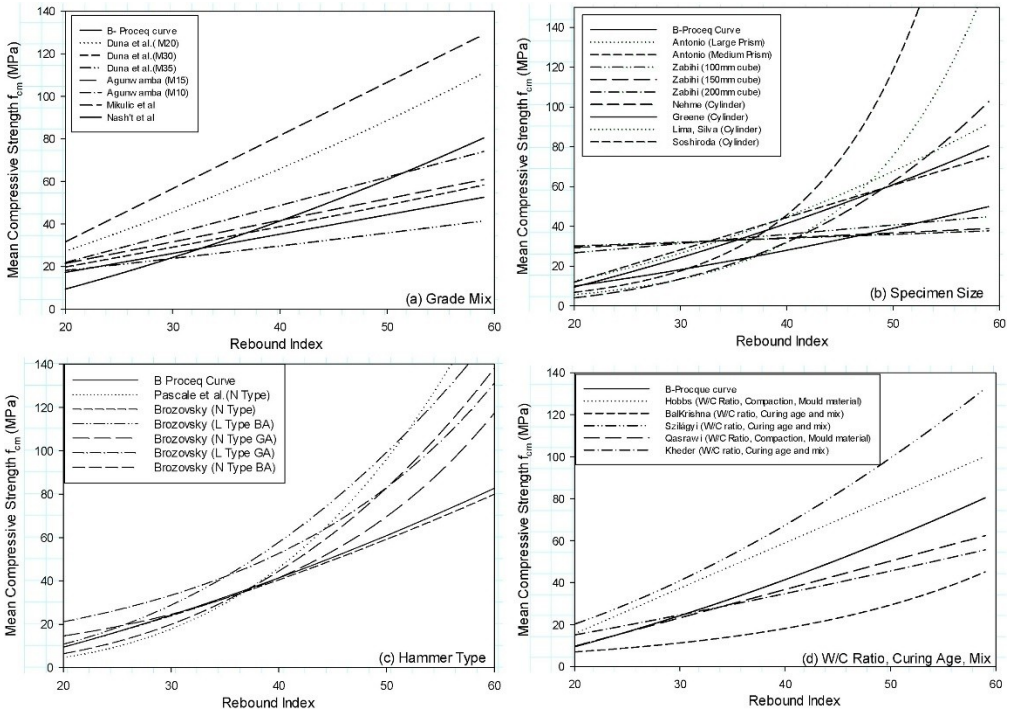



Figure 1.1.1 Rebound index vs. compressive strength relationship curves proposed by various authors considering different influencing factors. (Kumavat et al., 2021)

### *I.1.2 Past research related to the study*

Visual testing is the most important of all non-destructive tests. It can often provide valuable information to the well-trained eye. Visual features may be related to workmanship, structural serviceability, and material deterioration and it is particularly important that the engineer is able to differentiate between the various signs of distress which may be encountered. These include for instance, cracks, pop-outs, spalling, disintegration, color change, weathering, staining, surface blemishes and lack of uniformity.

Visual testing is the foremost necessary of all non-destructive tests. It will typically give valuable info to the well-trained eye. Visual options could also be associated with workmanship, structural usefulness, and material deterioration and it is significantly necessary that the engineer is able to differentiate between the varied signs of distress which can be encountered. These embrace as an example, cracks, pop-outs, spalling, disintegration, color change, weathering, staining, surface blemishes and lack of uniformity.

Extensive info is gathered from visual examination to convey a preliminary indication of the condition of the structure and permit formulation of a consequent testing program. The visual examination however must not be confined solely to the structure being investigated. It ought to conjointly embrace neighboring structures, the encircling environment, and the environmental condition. this can be the foremost tough facet of the full structural investigation or any diagnostic works since what seems obvious to at least one might not be thus to another.

The importance and advantages of a visual survey must not be underrated. typically, the omission of insignificant proof will cause a wrong conclusion being created. The advantage of a trained

eye is best represented by Sherlock Holmes when he wrote: “I see no more than you, however I have trained myself to note what I see.”(No, 2002)

(J.-I. Kim et al., 2004) has applied the custom of using neural networks with regards to destructive methods. The current study plans to do things differently by focusing on the non-destructive methods.

### *I.1.3 Theoretical issues of the study*

The study could theoretically have a problem with respect to which parameters should be included even with the addition of tools such as principal component analysis. This stems from the fact that aside from parameters such as mux design and the age of concrete, the other factors are sparingly found.

Considering that Machine learning needs lots of data, there could be a possibility that even with the vast amount of literature, the data would still not be enough. Machine learning needs lots of data since machine learning uses a lot of variables to create the model.

The gap from past studies is with regards to the fact that the influencing factors are analyzed in isolation. This study aims to improve on the literature with regards to how several factors

intermingle by creating a model. This would ideally be able to give insight as to the interaction of the concrete. The study also expands on the literature using ANN. The study uses MATLAB and its characteristics to create a model using ANN. The model would also be compared with regards to other models to ensure that using ANN would be helpful and to demonstrate the utility of ANN against other model types when the other model types have not been meticulously tweaked.

## I.2 Problem Statement

What is planned to be performed with regards to non-destructive testing and compressive strength is to look at the several factors that could influence the compressive strength of the concrete. This has been realized in the project by looking at how the properties such as amount of cement, fine and coarse aggregates used, and water content would affect the compressive strength of the concrete. The Primary component analysis was also used to help in the search for the most effective variables. The linear regression is also used to contribute to this search. The dataset was also segregated to those with NDT methods and those without to test the difference between including the methods and not including them. ANN processes the data to find

the best model to predict the compressive strength. This would be important to give generality to this research. These all would therefore give insight into the several factors of concrete compressive strength.

The input parameters that would be considered include: The concrete mix design, water-cement ratio, concrete age, rebound hammer and ultrasonic pulse velocity. Additonal factors that could affect are: Compaction used, Type of Aggregate used, Carbonation depth, Curing Condition and Moisture condition. (Kumavat et al., 2021) The output parameter would be the compressive strength of concrete.

The problem has been the inconsistency with respect to the different curve fitting results that an ultrasonic pulse velocity (UPV) test and rebound hammer test would give, namely the correlation between the pulse velocity and the rebound number with the compressive strength of the concrete, which is caused by the differences in the concrete used for calibration and the concrete used in the field (Kolaiti & Papadopoulos, 1993). This study aims to solve the problem by looking at different things that were done in performing the experiment and see how the difference in the conditions

of the concrete influenced the compressive strength of concrete.

## I.3 Objectives:

### *I.3.1 Main Objective*

To model the compressive strength of concrete obtained from non-destructive test using machine learning.

### *I.3.2 Specific Objectives*

To narrow down the search to factors that significantly contributed to the compressive strength of concrete.

To compare results using destructive methods with non-destructive methods.

Create a model using the factors to be considered.

## I.4 Hypothesis of the Study

The study was able to create a model to assist with the non-destructive testing of concrete.

The study was able to observe useful criteria in finding the compressive strength of concrete.

## I.5 Scope, Limitations, & Delimitations

The scope of the test would be the non-destructive methods in figuring out the compressive strength of the concrete.

The limitation would be with regards to the year of data obtainable. Although limited amounts of NDT are done in the 1930s, but the first disaster that would show NDT's necessity was in 1974, with the collapse of several high-alumina-cement pre-tensioned beams.(Maierhofer et al., 2010) Another consideration would be that many research papers are normally off-access, even with the multiple subscriptions acquired by DLSU. Although Sci-Hub allows access to most of the off-limits papers, their archives would be incomplete.

The delimitation is that the study has not focused on the destructive methods for testing concrete.

## I.6 Assumptions

The study would assume that the concrete from other studies has been prepared correctly, and that the data analysis is done correctly. The study also assumes that the code inside MATLAB is correct and corresponds to the correct algorithms. For example, it is assumed that the enabling Levenberg-Marquardt algorithm in the neural network fitting tool would make the weights and biases be updated with the correct implementation of Levenberg-Marquardt algorithm.

## I.7 Significance of the Study

The study would offer insight on what factors are the foremost vital when it involves deciding the compressive strength of the concrete. Moreover, the study considers the numerous factors that influences the done concrete tests. Looking at the various influencing factors is vital since it permits us to possess an improved understanding of what initial factors influence the compressive strength of the concrete.

Furthermore, the inclusion of NDT in this study has its benefits. Using NDT allows us to use concrete specimen that

have already been built and put to its proper use as one of the ways to predict compressive strength. This would be important since the values of NDT would allow us to measure how concrete stands up to the test of time. (Breysse, 2012)

# Chapter II

# Review of Related Literature

## II.1 Reinforced Concrete

### *II.1.1 What is concrete?*

Concrete is a mixture of aggregates and paste. Aggregates typically include sand and gravel or crushed stone. The paste in here typically refers to the combination of water and Portland Cement (Gagg, 2014). Concrete is also a widely used material in the world. (Crow, 2008)

Cement is a generic term that refers to all the binder materials for a concrete (Gagg, 2014).

### *II.1.2 What is reinforced concrete?*

Reinforced concrete consists of concrete and reinforcing bars. The reinforcing bars compensate for the fact that the concrete is weak in tension while strong in compression. (Condit, 1968)

### *II.1.3 Why use reinforced concrete?*

Reinforced concrete is better than wood in terms of fire

safety, sound insulation and acoustics, horizontal and vertical stability, and durability.(Hemström et al., 2011)

Reinforced concrete structures are also marginally more efficient in terms of limiting their CO2 emission when compared to structural steel. Moreover, Reinforced Concrete frames are also more efficient in terms of their energy consumption when compared to structural steel.(Ranjbar et al., 2021)

A counterargument, however, is with regards to the weaker inherent resistance of reinforced concrete with regards to earthquake loads. A wooden structure can withstand significant earthquakes loads without a need for a special consideration for earthquakes. Wood can deform more easily, and the light weight of the wood reduces the seismic forces inflicted to the building. This weakness could be fixed through the special design of reinforced concrete structures to withstand the earthquake loads.(Alih & Vafaei, 2019)

## II.2 Compressive strength of concrete

### *II.2.1 Importance of compressive strength of concrete*

Compressive strength is important because it is the strongest property of a concrete. The compressive strength of

concrete is 10 to 15% of its tensile and flexural strength, respectively. The fact that the concrete strength is related to the structure of the hydrated cement paste makes it a marker of concrete quality. For the reasons stated, compressive strength is used as a measure for the serviceability and strength of concrete structures and members.(Vu et al., 2020)

### *II.2.2 Factors affecting compressive strength*

The factors affecting compressive strength are: concrete mix design, water-cement ratio, concrete age, rebound hammer and ultrasonic pulse velocity. Additonal factors that could affect are: Compaction used, Type of Aggregate used, Carbonation depth, Curing Condition and Moisture condition (Kumavat et al., 2021).

Effect of substituting aggregates with recycled concrete aggregate with a same mix design has no difference in compressive strength (Latif Al-Mufti & Fried, 2012). Addition of rubber as aggregate has also been considered (Albano et al., 2005).

## II.3 Machine Learning

### *II.3.1 Usefulness of regression*

Regression is used to understand the relationships between different variables. Regression is used to find the causal effect between variables. Regression is useful for finding the effects of

various changes. (Sykes, n.d.) For this paper, regression is used to find the correlation between several factors and the compressive strength of concrete.

### *II.3.2 Different regression types*

Linear regression is a way to model the relationship between a scalar response and the exploratory variables. If there is only one independent variable and one dependent variable, then it is a simple linear regression. However, if there is more than one independent variable, then it would be called multiple linear regression. Multivariate linear regression is different for it includes multiple correlated dependent variables rather than a single dependent variable.(Freedman, 2009; Rencher & Christensen, 2012)

### *II.3.3 Definition of machine learning*

Machine learning concerns the usage of computer algorithms that continually improve based on data. This differs on what is traditionally done, wherein the model has to be explicitly created.(Friedman, 1998)

### *II.3.4 Regression and Machine Learning*

Linear regression could be used as a predecessor to the current methods used for machine learning. Even though it is less useful than contemporary methods, its simplicity allows us to quickly visualize the rationales for the different techniques that were used to ascend machine learning from a novelty to technique that would revolutionize the future. (Maulud & Abdulazeez, 2020)

## II.4 Non-destructive Methods of determining compressive strength

### *II.4.1 Destructive Methods*

Destructive methods are methods of collecting data that destroys the specimen that is used to collect the data (Făcăoaru, 1970). This contrasts with semi-destructive methods wherein the data collection process would cause cosmetic damage (Schabowicz, 2019).

Before there were non-destructive methods, there were destructive methods. The destructive methods are used as a baseline for they are the methods invented earlier (Schabowicz,

2019).

### *II.4.2 Non-destructive methods*

Non-destructive methods of measuring the compressive strength of concrete were made in response to concerns of safety of already built structures. The deterioration of these structures necessitated a way of observing the change between the initial state of the structure with its current state. (Helal et al., 2015)

The two most common methods for non-destructive testing are the rebound hammer test and Ultrasonic Pulse Velocity (UPV) test. (Malek & Kaouther, 2014)

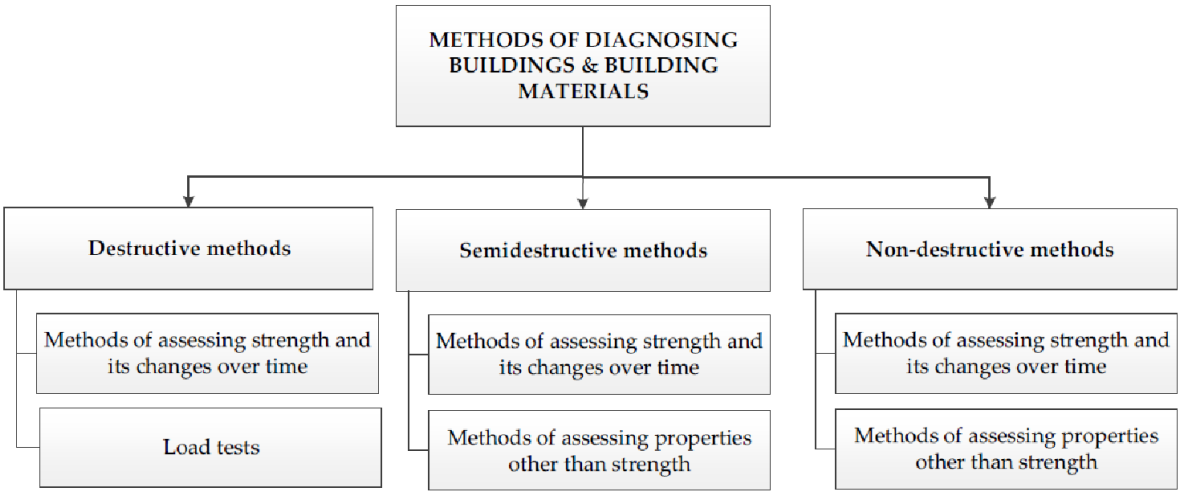

METHODS OF DIAGNOSING BUILDINGS & BUILDING MATERIALS
Destructive methods
Semidestructive methods
Non-destructive methods
Methods of assessing strength and its changes over time
Load tests
Methods of assessing strength and its changes over time
Methods of assessing properties other than strength
Methods of assessing strength and its changes over time
Methods of assessing properties other than strength

Figure 2.4.2 General classification of non-destructive methods

helpful for diagnosing buildings and building materials, grouped into destructive, semi-destructive and non-destructive. (Schabowicz, 2019)

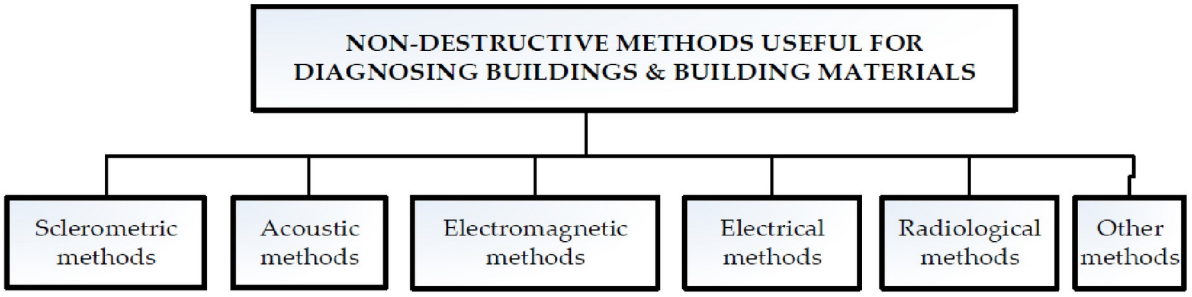



Figure 2.4.3 General classification of non-destructive methods beneficial for diagnosing buildings and building materials (Schabowicz, 2019)

## II.5 MATLAB

### *II.5.1 Use of MATLAB*

MATLAB is a software package that allows us to do mathematics and computing, analyze data, develop algorithms, and do simulation and modeling. The tool uses the MATLAB language.(Knight, 2000)

### *II.5.2 MATLAB Neural network toolbox*

One of the features of MATLAB is its support with regards to the different neural network algorithms. Most notably, its support with regards to the MATLAB neural network toolbox. (Ashour & Alqedra, 2005)

## II.6 PCA Analysis

Principal component analysis improves the analysis of neural networks.(Mohamad-Saleh & Hoyle, 2008)

## II.7 Similar Previous research

### *II.7.1 Applications of neural networks*

Sergio Lai and Mauro Serra used in 1997 neural networks to predict compressive strength. Destructive tests were used here (Lai & Serra, 1997). Neural networks were

also used to predict the slump and compressive strength of high strength concrete (Atici, 2011). Oztas et. al. also predicted the strength of a concrete using neural networks. (Öztaş et al., 2006)Neural networks have also been used to predict the properties of a dam as it is exposed to the elements for a long amount of time given the local conditions (Mata, 2011). The compressive strength of a no slump concrete was also estimated using neural networks. This paper also introduced adaptive network-based fuzzy inference systems (ANFIS) (Sobhani et al., 2010). Artificial neural networks and fuzzy logic are also used to calculate the properties of a rubberized concrete (Topçu & Sarıdemir, 2008).

Concrete cracks were also predicted using neural networks (Dung, 2019). Asphalt concrete permeability was also calculated using neural networks (Tarefder et al., 2005).

### *II.7.2 Other methods*

Fuzzy logic could also be used in the prediction of compressive strength of concrete.(Özcan et al., 2009)

## II.8 Related research on factors considered

### *II.8.1 Amount of cement in concrete*

The amount of cement influences the compressive strength of concrete (Raki et al., 2010). Thomas et. al. saw that the compressive strength would be higher as the amount of cement (kg/m^3) increases.(Thomas et al., 2018)

### *II.8.2 Amount of aggregate in concrete*

Quareshi et. al. used the mix proportion to check the behavior of the concrete. Namely, it is expected that decreasing the proportion of aggregates with respect to cement would increase the compressive strength of the concrete. It has also been found that the quality of the aggregates plays a significant role. (Qureshi et al., 2015)

### *II.8.3 Amount of recycled concrete aggregate in concrete*

It has been found that replacing up to 30% of the coarse aggregates to be used with RCA (Recycled Coarse Aggregate) would provide no significant difference in the compressive strength of concrete. Using above 30% replacement would decrease the compressive strength (Limbachiya et al., 2000). Thomas et. al. however, found that 25% of the coarse aggregates could be replaced with RCA (Thomas et al., 2018).

### *II.8.4 Amount of water content and water to binder ratio in concrete*

Thomas et. al. found that increasing the water to binder ratio would decrease the compressive strength of the concrete (Thomas et al., 2018). The water content could be found by multiplying the water binder ratio with the mass of binder per m^3 of concrete. Binders include materials such as concrete.

### *II.8.5 Amount of total unit weight in concrete*

The total unit weight in concrete has an influence. This is because the unit weight of concrete is due to the mix design. A lower unit weight is correlated with lower compressive strength and vice versa. Although it would seem beneficial to have a lower unit weight in order to make the structure lighter, the unit weight to be used for design is fixed and thus nonstandard procedures would be needed to exploit the lower weight of the synthesized concrete.(Mohammed et al., 2018; Mohammed & Adamu, 2019)

### *II.8.6 Amount of granite fines in concrete*

It has been found that it is optimal to replace 20% of the river sand with granite fines. However, it is also allowed to replace all the sand with granite fines wherever it would be more economical to us granite fines instead of sand. Sand is

also synonymous with fine aggregate. (Joel, 2010)

### *II.8.7 Amount of fly ash in concrete*

Fly ash can have pozzolanic properties and thus, it would be of interest to know how it contributes to the concrete. The effect of substituting Portland cement with fly ash has been analyzed. It has been found that using fly ash with fine particle sizes is a sufficient substitute. (Kiattikomol et al., 2001; Tangpagasit et al., 2005)

### *II.8.8 Amount of ground granulated blast furnace slag and nano silica in concrete*

It has been found that replacing 8% of the cement with nano silica would give the most optimal results; increasing the proportion of replacement would reduce the compressive strength of the concrete. The optimal percentage by which the cement would be replaced by slag is 70%. (Toutanji et al., 2004)

### *II.8.9 Amount of filler in concrete*

Fly ash, slag and other cementitious materials could be used as cementitious filler. (Mohammed et al., 2018; Mohammed & Adamu, 2019). Felekoğlu et. al. found that increasing the mineral filler replacing the cement to more

than 20% would cause the concrete to be weaker than the concrete without the substitution (Felekoğlu et al., 2006).

### *II.8.10 Amount of crumb rubber in concrete*

There have been investigations as to whether the addition of crumb rubber in concrete would affect its properties. It has been found that increasing the percentage of fine aggregate that would be replaced by crumb rubber would reduce its concrete strength. (Mohammed et al., 2018; Mohammed & Adamu, 2019)

### *II.8.11 Amount of metakaolin in concrete*

It has been seen that the amount of metakaolin has an influence on the compressive strength of concrete. A 10% replacement of cement with metakaolin is the most ideal replacement amount. Metakaolin, just like silica fumes, are a cementitious material used to replace a small part of cement (Poon et al., 2006). It has also been found that substituting cement with metakaolin is better than substituting a similar percentage of cement with silica fume.(Poon et al., 2006)

### *II.8.12 Amount of polypropylene fiber in concrete*

Ramujee performed research on the appropriate amount of fiver to place in the concrete. It has been found

that 1.5% by volume of concrete is the appropriate amount of fiber to use.(Ramujee, 2007)

### *II.8.13 Dry curing of concrete*

Atis et. al. has found that dry curing results in a lower compressive strength than wet curing. They have also found that concrete with silica fumes was more sensitive with regards to whether the concrete has been wet cured or dry cured. (Atiş et al., 2005)

### *II.8.14 Amount of superplasticizer in concrete*

It has been found that the amount of superplasticizer added to the concrete has, by itself, influence on the compressive strength of concrete. It has been found that a 1% ratio of superplasticizer is the most optimal. This proportion corresponds to adding 1000 ml of superplasticizer per 100 kg of cement added. (Alsadey, 2012)

### *II.8.15 Schmidt Rebound Number*

The Schmidt rebound number is a test that could be used to compare the compressive strength of concrete in the laboratory with the compressive strength of the concrete when deployed on site (Hannachi & Guetteche, 2014). However, even though using the manufacturer provided

conversion curve for Schmidt rebound number is not accurate for determining the compressive strength, the conservative nature of the curve should make it still sufficient to determine if the structure is safe. However, using the manufacturer provided curve would not give a reading that is accurate enough to deem the structure unsafe. Other methods would need to be used in order to determine if the structure is unsafe.(Sanchez & Tarranza, 2015)

### *II.8.16 Ultrasonic Pulse Velocity*

Ultrasonic pulse velocity is a reliable way of measuring the difference between the synthesis of the concrete with a given mix design on the lab and on the field. This is highlighted by the fact that a customized calibration curve would need to be created whenever a customized mix design would be used. It had also been found that the UPV is not that much affected by the type of cement or whether the aggregates were initially dry or wet.(Bogas et al., 2013)

### *II.8.17 Age of concrete*

The age of concrete matters since concrete matures and gets stronger in time through curing. This phenomenon could be seen in most of the studies with regards to concrete

(J.-I. Kim et al., 2004; J.-K. Kim et al., 1998). Therefore, it is standardized to choose the 28-day strength of concrete. This is the age when concrete is strong enough without the use of accelerators (Nurruddin & Department of Civil Engineering, Universiti Teknologi Petronas, Seri Iskandar, Malaysia, 2018).

# Chapter III

# Framework

## 3.1 Conceptual Framework

The data would be filtered out and separated into data that includes the all the non-destructive factors and one that does not. The data without all the non-destructive factors would have the remaining non-destructive test values further removed. To be more specific, the values of the NDT factors would be set to zero. On the figure, the data with NDT is the data with ultrasonic pulse velocity (UPV) and rebound number (RN). The data without NDT would be data without UPV and RN.

The data with NDTs would be used to create the primary component analysis (PCA), linear regression analysis, analysis using other models, and analysis using tweaked neural networks. The analysis using other models and linear regression analysis is useful for setting a baseline in terms of the mean squared error (MSE) of the model. This would make it much more likely to create a model that is better than the unoptimized versions of the other models, justifying the use of neural networks.

The primary component analysis and the linear regression analysis would be used to find the best NDT data. In this case, it would find the factors that would contribute the most to the compressive strength of concrete. The original data would then be again run into the analysis but this time, only the important factors would have values. The rest would be zeroed out. The analysis would produce NN, linear regression and other models. The other models would be to ensure that the MSE of the model would be low.

The data without NDT factors would be used to create the primary component analysis (PCA), linear regression analysis, analysis using other models, and analysis using tweaked neural networks. The analysis using other models and linear regression analysis is useful for setting a baseline in terms of the mean squared error (MSE) of the model. This would make it much more likely to create a model that is better than the unoptimized versions of the other models, justifying the use of neural networks.

The primary component analysis and the linear regression analysis would be used to find the best data without NDT. In this case, it would find the factors that would contribute the most to the compressive strength of concrete.

The original data would then be again run into the analysis but this time, only the important factors would have values. The rest would be zeroed out. The analysis would produce NN, linear regression and other models. The other models would be to ensure that the MSE of the model would be low.

The primary component analysis and the linear regressions would be used to narrow down to factors that significantly contribute to the compressive strength of concrete. The linear regressions are added in conjunction with the primary component analysis for the primary component analysis did not consider the non-destructive factors nor the age of concrete to contribute significantly to the compressive strength. The MATLAB has been used to create a model using the factors to be considered. The regression learner is used to test with regards to multiple models while the neural network fitting tool is used to tweak the neural network. The results of the models using non-destructive testing would be differentiated to those that did not using criteria such as MSE and r squared to compare results from destructive methods with non-destructive methods. These would determine if adding non-destructive test factors would improve accuracy. The three objectives are the requisite for modeling the

compressive strength of concrete from non-destructive tests using machine learning to be done. This is since the said objectives would be a guide to find the correct information about the matter and to explain the model derived.

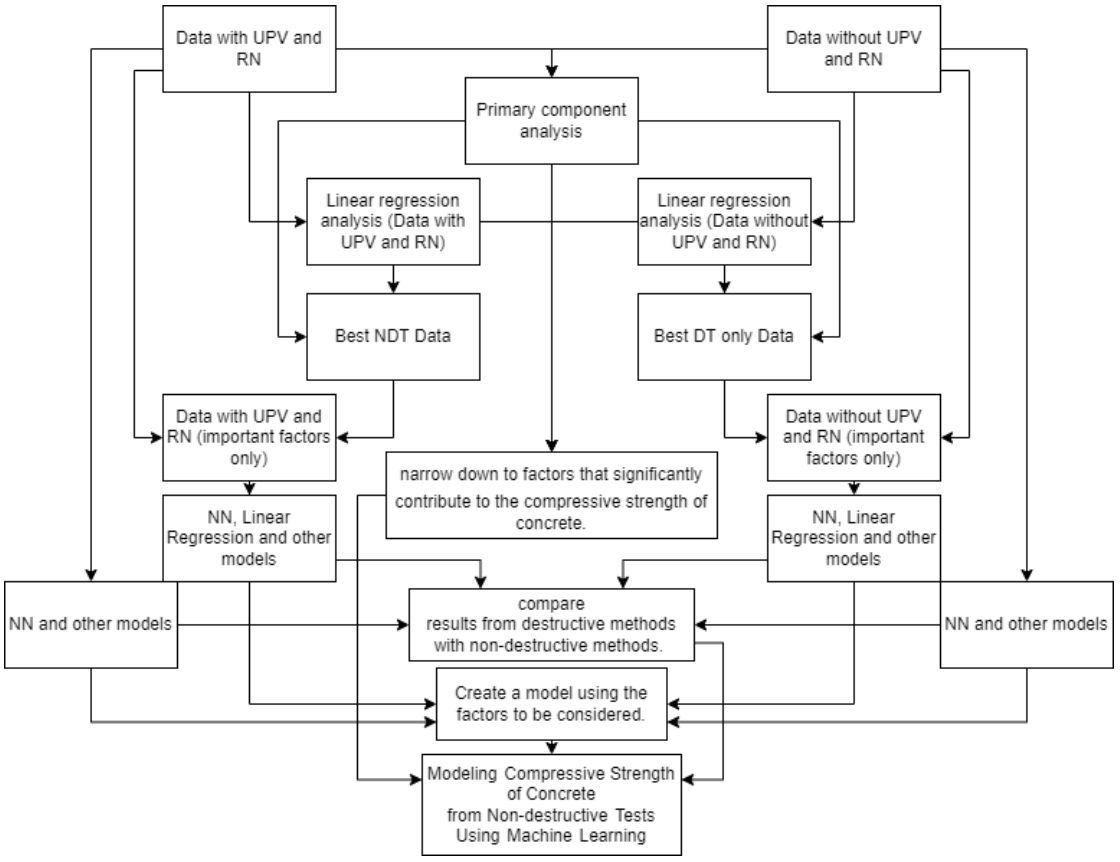

Data with UPV and RN
Data without UPV and RN
Primary component analysis
Linear regression analysis (Data with UPV and RN)
Linear regression analysis (Data without UPV and RN)
Best NDT Data
Best DT only Data
Data with UPV and RN (important factors only)
Data without UPV and RN (important factors only)
narrow down to factors that significantly contribute to the compressive strength of concrete.
NN, Linear Regression and other models
NN, Linear Regression and other models
NN and other models
compare results from destructive methods with non-destructive methods.
NN and other models
Create a model using the factors to be considered.
Modeling Compressive Strength of Concrete from Non-destructive Tests Using Machine Learning

Figure 3.1.4 Conceptual Framework

## 3.2 Theoretical Framework

### *III.1.1 Ultrasonic Pulse Velocity Test*

An ultrasonic pulse velocity (UPV) test is an in-situ, nondestructive test to check the quality of concrete. In this test, the strength and quality of concrete is assessed by measuring the velocity of an ultrasonic pulse passing through a concrete structure.

This test is conducted by passing a pulse of ultrasonic through concrete to be tested and measuring the time taken by pulse to get through the structure. Higher velocities indicate decent quality and continuity of the material, while slower velocities may indicate concrete with many cracks or voids.

Ultrasonic testing equipment includes a pulse generation circuit, consisting of electronic circuit for generating pulses and a transducer for transforming electronic pulse into mechanical pulse having an oscillation frequency in range of 40 kHz to 50 kHz, and a pulse reception circuit that receives the signal.(Amini et al., 2016)

### *III.1.2 Rebound Number*

Rebound Hammer test is a Non-destructive testing

technique of concrete which offer a convenient and speedy indication of the compressive strength of the concrete. The rebound hammer is additionally referred to as Schmidt hammer that comprises a spring-controlled mass that slides on a plunger inside a tubular housing. once the plunger of rebound hammer is ironed against the surface of concrete, a spring-controlled mass with a continuing energy is formed to hit concrete surface to rebound back. The extent of rebound, that is a measure of surface hardness, is measured on a graduated scale. This measured value is selected as Rebound number (rebound index). Concrete with low strength and low stiffness will absorb additional energy to yield in a lower rebound value.(Szilagyi & Borosnyoi, 2009)

### *III.1.3 Artificial neural network*

The study will use an Artificial Neural Network (ANN) to model the compressive strength. The idea would be to leverage the currently existing literature on the internet to perform the technique. Data could be found by asking or by leveraging graphs provided in the journals.

An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the

synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron receives a signal then processes it and signals neurons connected to it. The "signal" at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. The connections are called edges. Neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer (the input layer) to the last layer (the output layer), possibly after traversing the layers multiple times. (Schmidhuber, 2015)

#### III.1.3.1 Typical Tweaked Neural Network Code

```
function [Y,Xf,Af] = myNeuralNetworkFunction(X,~,~)
%{
MYNEURALNETWORKFUNCTION neural network simulation function.

Auto-generated by MATLAB, 17-Jul-2022 23:44:26.

[Y] = myNeuralNetworkFunction(X,~,~) takes these arguments:
  X = 1xTS cell, 1 inputs over TS timesteps
  Each X{1,ts} = 21xQ matrix, input #1 at timestep ts.

and returns:
```

```
  Y = 1xTS cell of 1 outputs over TS timesteps.
  Each Y{1,ts} = 1xQ matrix, output #1 at timestep ts.

where Q is number of samples (or series) and TS is the number of
timesteps.
%}

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.keep = [1 2 3 4 5 6 8 9 10 11 13 14 15 18 19 20];
x1_step2.xoffset =
[0;0;0;0;0;35;1285.5;0;0;0;0;0;0;0;14;2.93890080756283];
x1_step2.gain =
[0.00389105058365759;0.00155038759689922;0.00173897921919
833;0.00306748466257669;0.002439024390243 9;0.008264462809
91736;0.00177856825255669;0.0060716454159 0771;0.004;0.0097
799511002445;0.0192492781520693;0.00579206487112656;0.004
;0.571428571428571;0.0526868947757209;0.869905920796697];
x1_step2.ymin = -1;

% Layer 1
b1 = -0.70923997426089013807;
IW1_1 = [0.021014363643190939 19 -0.32680399700141615771 -
0.35375752065656462797 -0.17799997068152467738 -
0.23245902704647211645 0.15110307686759430479
0.35888284222173832 96 -0.11807944164896123918 -
0.008405623100206489 8949 -0.09788586907040383589
0.20962362381938187683 0.028691738122860604987 -
0.21873183093228723561 0.362844900999798825 05
0.28180062653067688982 0.190395591700141558 76];

% Layer 2
b2 = 0.20107515242795612198;
LW2_1 = 1.594985355110133618;

% Output 1
y1_step1.ymin = -1;
y1_step1.gain = 0.0286728785406686;
y1_step1.xoffset = 11.117673;

% ===== SIMULATION ========

% Format Input Arguments
```

```
isCellX = iscell(X);
if ~isCellX
    X = {X};
end

% Dimensions
TS = size(X,2); % timesteps
if ~isempty(X)
    Q = size(X{1},2); % samples/series
else
    Q = 0;
end

% Allocate Outputs
Y = cell(1,TS);

% Time loop
for ts=1:TS

    % Input 1
    temp = removeconstantrows_apply(X{1,ts},x1_step1);
    Xp1 = mapminmax_apply(temp,x1_step2);

    % Layer 1
    a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*Xp1);

    % Layer 2
    a2 = repmat(b2,1,Q) + LW2_1*a1;

    % Output 1
    Y{1,ts} = mapminmax_reverse(a2,y1_step1);
end

% Final Delay States
Xf = cell(1,0);
Af = cell(2,0);

% Format Output Arguments
if ~isCellX
    Y = cell2mat(Y);
end
end

% ===== MODULE FUNCTIONS ========
```

```
% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings)
y = (x - settings.xoffset) .* settings.gain + settings.ymin;
end

% Remove Constants Input Processing Function
function y = removeconstantrows_apply(x,settings)
y = x(settings.keep,:);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1;
end

% Map Minimum and Maximum Output Reverse-Processing Function
function x = mapminmax_reverse(y,settings)
x = (y - settings.ymin) ./ settings.gain + settings.xoffset;
end
```

# Chapter IV

# Research Methodology

## IV.1 Research Method

The research was performed using MATLAB to process the data. Web Plot Digitizer was used to help convert the points within the charts into tabular data. The data was collected from journals and other reliable sources.

### *IV.1.1 Input and tool and techniques (ITTO) and further explanation for each of the objectives*

Create a model using the factors to be considered. The inputs are going to be the factors to be considered. The tools and techniques are the methods that are going to be used for gathering the factors and the machine learning algorithm itself. The output would be a model, a description of how the concrete strength using the factors.

To narrow down the search to factors that significantly contributed to the compressive strength of concrete. This is useful to understand which parameters created a meaningful

change to the compressive strength of concrete. The inputs have been the factors to be considered. The tools and techniques were principal component analysis and feature elimination. The objective was to have a smaller set of features.

To compare results from destructive methods with non-destructive methods. The input would be the results from destructive methods with non-destructive methods, more specifically the same inputs as used for the non-destructive tests. This would be used to gauge the extent by which the results are different using non-destructive testing than destructive testing. The tools and techniques are the methods that are going to be used for gathering the factors and the machine learning algorithm itself. This is like the case with non-destructive concrete since it would both need a similar approach. The output would be a separate model considering only destructive concrete measurements. This would be used to compare one against the other. Note that a separate model needs to be created for non-destructive testing simply to compare itself against destructive tests due to the difference in factors.

## IV.2 Research Design

The data that was used is the previous research in the field of non-destructive testing that tried to find out the compressive strength of a concrete using non-destructive methods.

## IV.3 Data Cleansing

The graph that was placed on Web Plot Digitizer was cleaned by removing formulas in the pictures of charts. Outrageous values from the same program were removed. Visual inspection was used to filter out discrepant points.

## IV.4 Collection of data

The first step was to acquire data from various journals. The journals considered included the following:

Table 4.4-1 Table of journals considered for addition

| Author | Title | Publication Title | Vol. | Issue | Publication Year |
|---|---|---|---|---|---|
| Noori, Ali S.; Oweed, Khalid M.; Raouf, Raouf M.; Abdulrehman, Mohammed A. | The relation between destructive and non-destructive tests of geopolymer concrete | Materials Today: Proceedings | 42 | 0 | 2021 |
| Latif Al-Mufti, R.; Fried, A.N. | The early age non-destructive testing of concrete made with recycled concrete aggregate | Construction and Building Materials | 37 | 0 | 2012 |
| Alwash, Maitham; Sbartaï, Zoubir Mehdi; Breysse, Denys | Non-destructive assessment of both mean strength and variability of concrete: A new bi-objective approach | Construction and Building Materials | 113 | 0 | 2016 |
| Ivanchev, Ivan | Experimental Determination of Modulus of Elasticity of Concrete by Non-Destructive Ultrasonic Pulse Velocity Method | Int. J. Res. Appl. Sci. Eng. Technol | 6 | 0 | 2018 |

| Author | Title | Publication Title | Vol. | Issue | Publication Year |
|---|---|---|---|---|---|
| Malek, Jedidi; Kaouther, Machta | Destructive and Non-destructive Testing of Concrete Structures | Jordan Journal of Civil Engineering | 8 | 4 | 2014 |
| Poorarbabi, Ali; Ghasemi, Mohammadreza; Azhdary Moghaddam, Mehdi | Concrete compressive strength prediction using non-destructive tests through response surface methodology | Ain Shams Engineering Journal | 11 | 4 | 2020 |
| Amini, Kamran; Jalalpour, Mehdi; Delatte, Norbert | Advancing concrete strength prediction using non-destructive testing: Development and verification of a generalizable model | Construction and Building Materials | 102 | 0 | 2016 |
| Singh, Navdeep; Singh, S. P. | Evaluating the performance of self-compacting concretes made with recycled coarse and fine aggregates | Construction and Building Materials | 181 | 0 | 2018 |

| Author | Title | Publication Title | Vol. | Issue | Publication Year |
|---|---|---|---|---|---|
| | using non-destructive testing techniques | | | | |
| Velay-Lizancos, Mirian; Martinez-Lage, Isabel; Azenha, Miguel; Granja, Jose; Vazquez-Burgo, Pablo | Concrete with fine and coarse recycled aggregates: E-modulus evolution, compressive strength, and non-destructive testing at early ages | Construction and Building Materials | 193 | 0 | 2018 |
| Aseem, Ahmed; Baloch, Waqas Latif; Khushnood, Rao Arsalan; Mushtaq, Arslan | Structural health assessment of fire damaged building using non-destructive testing and micro-graphical forensic analysis: a case study | Case Studies in Construction Materials | 11 | 0 | 2019 |
| Asteris, Panagiotis G.; Mokos, Vaseilios G. | Concrete compressive strength using artificial neural networks | Neural Computing and Applications | 32 | 15 | 2020 |
| Jasiński, Rados\law; | Validation of selected non- | Materials | 12 | 3 | 2019 |

| Author | Title | Publication Title | Vol. | Issue | Publication Year |
|---|---|---|---|---|---|
| Drobiec, \ Lukasz; Mazur, Wojciech | destructive methods for determining the compressive strength of masonry units made of autoclaved aerated concrete | | | | |
| Rahim, Mustaqqim Abdul; Shahidan, Shahiron; Lee, Choon Onn; Bahari, Nur Amira Afiza Saiful; Abd Rahman, Norashidah; Ayob, Afizah | The behavior of non-destructive test for different grade of concrete | International Journal of Integrated Engineering | 12 | 9 | 2020 |
| Wolfs, R. J. M.; Bos, F. P.; Salet, T. A. M. | Correlation between destructive compression tests and non-destructive ultrasonic measurements on early age 3D printed concrete | Construction and Building Materials | 181 | 0 | 2018 |
| Kovler, Konstantin; Wang, Fengzhe; Muravin, Boris | Testing of concrete by rebound method: Leeb versus Schmidt | Materials and Structures | 51 | 5 | 2018 |

| Author | Title | Publication Title | Vol. | Issue | Publication Year |
|---|---|---|---|---|---|
| | hammers | | | | |
| Mohammed, Bashar S.; Adamu, Musa; Liew, Mohd Shahir | Evaluating the effect of crumb rubber and nano silica on the properties of high-volume fly ash roller compacted concrete pavement using non-destructive techniques | Case studies in construction materials | 8 | 0 | 2018 |
| Tan, Yongshan; Yu, Hongfa; Mi, Renjie; Zhang, Yan | Compressive strength evaluation of coral aggregate seawater concrete (CAC) by non-destructive techniques | Engineering Structures | 176 | 0 | 2018 |
| Tchamdjou, Willy H. Juimo; Cherradi, Toufik; Abidi, Moulay Larbi; Pereira-de-Oliveira, Luiz A. | Mechanical properties of lightweight aggregates concrete made with cameroonian volcanic scoria: Destructive and non-destructive characterization | Journal of Building Engineering | 16 | 0 | 2018 |
| Mohammed, Bashar S.; Adamu, Musa | Non-destructive evaluation of | Road Materials and | 20 | 4 | 2019 |

| Author | Title | Publication Title | Vol. | Issue | Publication Year |
|---|---|---|---|---|---|
| | nano silica-modified roller-compacted rubbercrete using combined SonReb and response surface methodology | Pavement Design | | | |
| Kazemi, Mostafa; Madandoust, Rahmat; de Brito, Jorge | Compressive strength assessment of recycled aggregate concrete using Schmidt rebound hammer and core testing | Construction and Building Materials | 224 | 0 | 2019 |
| Sreenivasulu, C.; Guru Jawahar, J.; Sashidhar, C. | Predicting compressive strength of geopolymer concrete using NDT techniques | Asian Journal of Civil Engineering | 19 | 4 | 2018 |

From the following table, here are the journals that were included in the dataset:

Table 4.4-2 Table of journals added in the dataset

| Author | Title | Publication Title | Publication Year |
|---|---|---|---|
| Noori, Ali S.; Oweed, Khalid M.; Raouf, Raouf M.; Abdulrehman, Mohammed A. | The relation between destructive and non-destructive tests of geopolymer concrete | Materials Today: Proceedings | 2021 |
| Poorarbabi, Ali; Ghasemi, Mohammadreza; Azhdary Moghaddam, Mehdi | Concrete compressive strength prediction using non-destructive tests through response surface methodology | Ain Shams Engineering Journal | 2020 |
| Singh, Navdeep; Singh, S. P. | Evaluating the performance of self-compacting concretes made with recycled coarse and fine aggregates using non-destructive testing techniques | Construction and Building Materials | 2018 |
| Rahim, Mustaqqim Abdul; Shahidan, Shahiron; Lee, Choon Onn; Bahari, Nur Amira Afiza Saiful; Abd Rahman, Norashidah; Ayob, Afizah | The behavior of non-destructive test for different grade of concrete | International Journal of Integrated Engineering | 2020 |

| Author | Title | Publication Title | Publication Year |
|---|---|---|---|
| Kovler, Konstantin; Wang, Fengzhe; Muravin, Boris | Testing of concrete by rebound method: Leeb versus Schmidt hammers | Materials and Structures | 2018 |
| Mohammed, Bashar S.; Adamu, Musa; Liew, Mohd Shahir | Evaluating the effect of crumb rubber and nano silica on the properties of high-volume fly ash roller compacted concrete pavement using non-destructive techniques | Case studies in construction materials | 2018 |
| Mohammed, Bashar S.; Adamu, Musa | Non-destructive evaluation of nano silica-modified roller-compacted rubbercrete using combined SonReb and response surface methodology | Road Materials and Pavement Design | 2019 |
| Kazemi, Mostafa; Madandoust, Rahmat; de Brito, Jorge | Compressive strength assessment of recycled aggregate concrete using Schmidt rebound hammer and core testing | Construction and Building Materials | 2019 |

| Author | Title | Publication Title | Publication Year |
|---|---|---|---|
| Sreenivasulu, C.; Guru Jawahar, J.; Sashidhar, C. | Predicting compressive strength of geopolymer concrete using NDT techniques | Asian Journal of Civil Engineering | 2018 |

There were also journals that showed promise, but the data has not been planned to be included since the mix design used to create the data was not found:

Table 4.4-3 Table of journals not included and their reasons for non-inclusion

| Author | Title | Publication Title | Reason for non-inclusion |
|---|---|---|---|
| Latif Al-Mufti, R.; Fried, A.N. | The early age non-destructive testing of concrete made with recycled concrete aggregate | Construction and Building Materials | weight of cement etc. could not be found in text |
| Alwash, Maitham; Sbartaï, Zoubir Mehdi; | Non-destructive assessment of both mean strength and | Construction and Building Materials | no mix design |

| Author | Title | Publication Title | Reason for non-inclusion |
|---|---|---|---|
| Breysse, Denys | variability of concrete: A new bi-objective approach | | |
| Ivanchev, Ivan | Experimental Determination of Modulus of Elasticity of Concrete by Non-Destructive Ultrasonic Pulse Velocity Method | Int. J. Res. Appl. Sci. Eng. Technol | EN 12390-2:2009 Accessible; I. Dobreva inaccessible |
| Amini, Kamran; Jalalpour, Mehdi; Delatte, Norbert | Advancing concrete strength prediction using non-destructive testing: Development and verification of a generalizable model | Construction and Building Materials | no mix data |
| Asteris, Panagiotis G.; Mokos, Vaseilios G. | Concrete compressive strength using artificial neural networks | Neural Computing and Applications | meta-source paper (Logothetis LA (1978)) not found |
| Wolfs, R. J. M.; Bos, F. P.; Salet, T. A. M. | Correlation between destructive compression tests and non-destructive | Construction and Building Materials | proprietary materials |

| Author | Title | Publication Title | Reason for non-inclusion |
|---|---|---|---|
| | ultrasonic measurements on early age 3D printed concrete | | |
| Tan, Yongshan; Yu, Hongfa; Mi, Renjie; Zhang, Yan | Compressive strength evaluation of coral aggregate seawater concrete (CAC) by non-destructive techniques | Engineering Structures | mix proportion abstracted from results |

From there, the data that have been found from the selected sources has been combined into a table. The table contains the following variables:

- Cement (kg/m^3)
- Coarse aggregates (kg/m^3)
- Fine aggregates (kg/m^3)
- Coarse RCA (kg/m^3)
- Fine RCA (kg/m^3)

- Water content (kg/m^3)
- Water to binder ratio
- Total Unit Weight (kg/m^3)
- Granite Fines (kg/m^3)
- Fly ash content (kg/m^3)
- Ground Granulated Blast Furnace Slag (GGBS) (kg/m^3)
- Nano Silica (kg/m^3)
- Filler (kg/m^3)
- Crumb Rubber (kg/m^3)
- Metakaolinite Content (kg/m^3)
- polypropylene fibre (% by volume)
- dry curing
- Superplasticizer (%)
- Age of concrete (days)
- Compressive strength (MPa)

The missing data would be filled whenever it is reasonable to have it filled. For instance, the studies that do not use granite fines would have 0 kg/m^3 of granite fines in their concrete. Missing data by which there is no suitable value to add to the missing data would be left as blank.

The data (which would be placed in a table) would then be filtered out. The columns in the table would have the relevant filters added then moved to another set of cells. This is done to remove entries with missing data (that has not been filled up) with regards to the columns (factors) that would be used.

The data would then be exported into MATLAB. The way to do it is to access the workbook with the relevant data using MATLAB. This would give a wizard by which data could be imported as a MATLAB table.

To create the numerical arrays needed for Neural Net Fitting tool under the Deep Learning Toolbox, two numerical arrays are created, one which has the inputs, which are the factors that are theorized to influence the compressive strength and the other is the output, which is the compressive strength itself.

The MATLAB table would then be inputted to the Regression Learner tool to use all the available models in Regression Learner tool at default settings to test the data. A model that would be sent for further analysis would be the model with the lowest root mean squared error (RMSE) using the validation dataset. The other model that would be sent for further analysis would be the linear regression and the neural network which has the lowest RMSE. The linear regression is sent for further analysis since it would be easy to interpret; the value predicted by the regression could be found by summing the product of the regression coefficients with the input variable and adding to it the regression intercept. The neural network would be used for the sake of comparison. The neural network by which the size of the hidden layers has been optimized to bring a better result is expected to be better than an unoptimized neural network.

The Regression Learner tool could also be used to find the primary components, the set of components that would be able to explain 95% of the variance of the model. In other words, the factors could be summed up into a smaller set of primary components that could explain 95% of the changes with regards to the data.

The primary components could then be used to find out the factors that influence the compressive strength of concrete the most. The idea with the analysis is that if the factor has a greater than 5% contribution to the principal components on average, then the factor is construed to be important since they have a considerable contribution to the principal components, which would imply that the factor contributes appreciably to the variation of data, in that the compressive strength is changed remarkably by the influence of the factor shortlisted.

The numerical arrays would then be used as the inputs and the outputs of the artificial neural network. The hidden layer of the neural network would be modified until the model is able to reach close to an equilibrium with regards to train mean squared error (MSE) prevailing or the validation MSE is prevailing. The ideal hidden neural network is one where the train, test, and validation MSE is as similar as they could be while the MSE is smaller than the other techniques analyzed. Once the ideal neural network has been found, the results of the neural network are analyzed further. Further analysis includes extracting relevant tables and graphs from the model and extraction of the created model itself, such that it could

be used to predict future data.

The different methods are going to be tabulated with regards to their R-Squared and MSE. This is to ensure that model found fits the criteria that would be needed to say that the model found is optimal.

## IV.5 Summary of Procedures

The flow of the study begins by looking at the different journal articles. The data from the articles could be sourced using tables of the data, if available, or by using web plot digitizer. The web plot digitizer would make the extraction of the data easier by making it less error prone. It would allow less error by having the software pick out the data and put it in a spreadsheet. There would also need to be some fiddling so that the figures would be seen correctly and some manual inclusion of points in some circumstances.

This all would allow me to have the data from journal articles. After all this, I would compile the data based on all the factors considered. I would also fill the missing data afterwards, taking note to fill data only when reasonable and

to leave unfilled data blank.

After this, the data would be filtered out and separated into data that includes the all the non-destructive factors and one that does not. The data without all the non-destructive factors would have the remaining non-destructive test values further removed. To be more specific, the values of the NDT factors would be set to zero. On the figure, the data with NDT is the data with ultrasonic pulse velocity (UPV) and rebound number (RN). The data without NDT would be data without UPV and RN.

The data with NDTs would be used to create the primary component analysis (PCA), linear regression analysis, analysis using other models, and analysis using tweaked neural networks. The analysis using other models and linear regression analysis is useful for setting a baseline in terms of the mean squared error (MSE) of the model. This would make it much more likely to create a model that is better than the unoptimized versions of the other models, justifying the use of neural networks.

The primary component analysis and the linear regression analysis would be used to find the best NDT data.

In this case, it would find the factors that would contribute the most to the compressive strength of concrete. The original data would then be again run into the analysis but this time, only the important factors would have values. The rest would be zeroed out. The analysis would produce NN, linear regression and other models. The other models would be to ensure that the MSE of the model would be low.

The data without NDT factors would be used to create the primary component analysis (PCA), linear regression analysis, analysis using other models, and analysis using tweaked neural networks. The analysis using other models and linear regression analysis is useful for setting a baseline in terms of the mean squared error (MSE) of the model. This would make it much more likely to create a model that is better than the unoptimized versions of the other models, justifying the use of neural networks.

The primary component analysis and the linear regression analysis would be used to find the best data without NDT. In this case, it would find the factors that would contribute the most to the compressive strength of concrete. The original data would then be again run into the analysis but this time, only the important factors would have values.

The rest would be zeroed out. The analysis would produce NN, linear regression and other models. The other models would be to ensure that the MSE of the model would be low.

The best model would be decided based on the MSE of the NNs that have factors removed. This is because the reduced models are sufficiently good when compared to the unreduced versions. Comparing the models with NDT factors to those without NDT factors is also to see how NDT factors would influence the model.

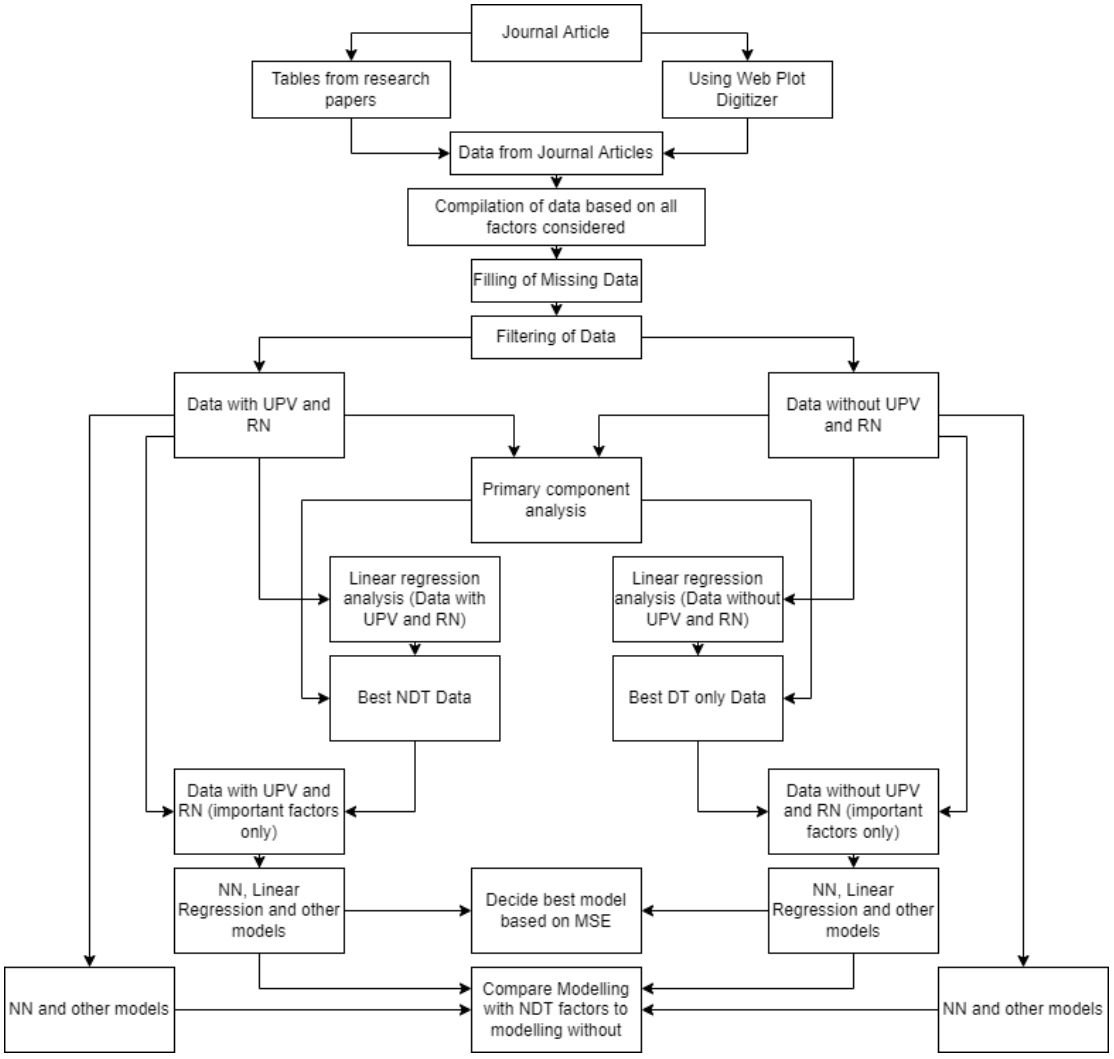

Journal Article
Tables from research papers
Using Web Plot Digitizer
Data from Journal Articles
Compilation of data based on all factors considered
Filling of Missing Data
Filtering of Data
Data with UPV and RN
Data without UPV and RN
Primary component analysis
Linear regression analysis (Data with UPV and RN)
Linear regression analysis (Data without UPV and RN)
Best NDT Data
Best DT only Data
Data with UPV and RN (important factors only)
Data without UPV and RN (important factors only)
NN, Linear Regression and other models
Decide best model based on MSE
NN, Linear Regression and other models
NN and other models
Compare Modelling with NDT factors to modelling without
NN and other models

Figure 4.5.5 Summary of research

# Chapter V

## Results and Discussion

### V.1 Primary Component Analysis

The primary component analysis was performed to find out which of the variables were most impactful for the analysis. Primary component analysis would be useful since it would be able to see which of the factors contribute the most to the models.

Table 5.1-4 Breakdown using primary component analysis.

| Labels | PC1 | PC2 | PC3 | PC4 | PC5 |
|---|---|---|---|---|---|
| Cement (kg/m^3) | -0.1997 | 0.0066 | 0.0345 | -0.5607 | 0.4879 |
| Coarse aggregates (kg/m^3) | -0.7429 | -0.2102 | -0.4345 | -0.113 | 0.0785 |
| Fine aggregates (kg/m^3) | -0.0683 | 0.8883 | -0.1492 | 0.0648 | -0.0588 |
| Coarse RCA (kg/m^3) | -0.0341 | -0.1721 | 0.4477 | 0.5786 | 0.4066 |
| Fine RCA (kg/m^3) | -0.0176 | -0.1089 | 0.5371 | -0.4535 | -0.4396 |
| Water content (kg/m^3) | -0.0991 | -0.0697 | 0.0783 | -0.0853 | -0.0256 |
| Water to binder ratio | -0.0003 | -0.0002 | 0.0001 | 0 | -0.0002 |
| Total Unit Weight (kg/m^3) | 0.6113 | 0.3357 | 0.5385 | -0.0698 | 0.1157 |
| Granite Fines (kg/m^3) | -0.0301 | -0.0193 | -0.0029 | 0.0559 | -0.0924 |
| Fly ash content (kg/m^3) | 0.102 | -0.0161 | 0.0373 | 0.3166 | -0.3234 |
| Ground Granulated Blast Furnace Slag | -0.0371 | -0.0169 | -0.0064 | 0.0701 | -0.1108 |

| | | | | | |
|---|---|---|---|---|---|
| (GGBS) (kg/m^3) | | | | | |
| Nano Silica (kg/m^3) | 0.0011 | 0.0018 | 0.0006 | -0.0007 | 0.0075 |
| Filler (kg/m^3) | 0.0298 | 0.0507 | 0.016 | -0.0181 | 0.2051 |
| Crumb Rubber (kg/m^3) | 0.0463 | 0.0622 | 0.0194 | -0.0381 | 0.4534 |
| Metakaolinite Content (kg/m^3) | 0.0516 | 0.0085 | -0.0179 | 0.0778 | -0.0788 |
| polypropylene fibre (% by volume) | 0 | 0 | 0 | 0 | 0 |
| dry curing | 0 | 0 | 0 | 0 | 0 |
| Superplasticizer (%) | 0.0013 | -0.0001 | -0.0003 | 0.0029 | -0.0039 |
| (Schmidt) Rebound number | 0.0073 | -0.0004 | 0.009 | -0.0023 | 0.0117 |
| UPV (km/s) | -0.0002 | 0.0001 | 0.0002 | -0.0013 | 0.0017 |
| Age of concrete (days) | -0.008 | -0.016 | 0.0137 | -0.0023 | -0.0141 |
| Compressive strength (MPa) | | | | | |

The primary components were chosen by creating as many principal components as needed to explain 95% of the variance in the data. The analysis was able to see that five principal components are only needed.

Table 5.1-5 The values showing the sum of the multiplier applied to the principal components. The values in green are those whose sum is greater than 0.25

| Absolute value of Primary Components | PC1 | PC2 | PC3 | PC4 | PC5 | Sum | Rank of sums |
|---|---|---|---|---|---|---|---|
| Cement (kg/m^3) | 0.1997 | 0.0066 | 0.0345 | 0.5607 | 0.4879 | 1.2894 | 5 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Coarse aggregates (kg/m^3) | 0.7429 | 0.2102 | 0.4345 | 0.113 | 0.0785 | 1.5791 | 3 |
| Fine aggregates (kg/m^3) | 0.0683 | 0.8883 | 0.1492 | 0.0648 | 0.0588 | 1.2294 | 6 |
| Coarse RCA (kg/m^3) | 0.0341 | 0.1721 | 0.4477 | 0.5786 | 0.4066 | 1.6391 | 2 |
| Fine RCA (kg/m^3) | 0.0176 | 0.1089 | 0.5371 | 0.4535 | 0.4396 | 1.5567 | 4 |
| Water content (kg/m^3) | 0.0991 | 0.0697 | 0.0783 | 0.0853 | 0.0256 | 0.358 | 9 |
| Water to binder ratio | 0.0003 | 0.0002 | 0.0001 | 0 | 0.0002 | 0.0008 | 19 |
| Total Unit Weight (kg/m^3) | 0.6113 | 0.3357 | 0.5385 | 0.0698 | 0.1157 | 1.671 | 1 |
| Granite Fines (kg/m^3) | 0.0301 | 0.0193 | 0.0029 | 0.0559 | 0.0924 | 0.2006 | 13 |
| Fly ash content (kg/m^3) | 0.102 | 0.0161 | 0.0373 | 0.3166 | 0.3234 | 0.7954 | 7 |
| Ground Granulated Blast Furnace Slag (GGBS) (kg/m^3) | 0.0371 | 0.0169 | 0.0064 | 0.0701 | 0.1108 | 0.2413 | 11 |
| Nano Silica (kg/m^3) | 0.0011 | 0.0018 | 0.0006 | 0.0007 | 0.0075 | 0.0117 | 16 |
| Filler (kg/m^3) | 0.0298 | 0.0507 | 0.016 | 0.0181 | 0.2051 | 0.3197 | 10 |
| Crumb Rubber (kg/m^3) | 0.0463 | 0.0622 | 0.0194 | 0.0381 | 0.4534 | 0.6194 | 8 |
| Metakaolinite Content (kg/m^3) | 0.0516 | 0.0085 | 0.0179 | 0.0778 | 0.0788 | 0.2346 | 12 |
| polypropylene fibre (% by volume) | 0 | 0 | 0 | 0 | 0 | 0 | 21 |
| dry curing | 0 | 0 | 0 | 0 | 0 | 0 | 21 |
| Superplasticizer (%) | 0.0013 | 0.0001 | 0.0003 | 0.0029 | 0.0039 | 0.0085 | 17 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| (Schmidt) Rebound number | 0.0073 | 0.0004 | 0.009 | 0.0023 | 0.0117 | 0.0307 | 15 |
| UPV (km/s) | 0.0002 | 0.0001 | 0.0002 | 0.0013 | 0.0017 | 0.0035 | 18 |
| Age of concrete (days) | 0.008 | 0.016 | 0.0137 | 0.0023 | 0.0141 | 0.0541 | 14 |
| Compressive strength (MPa) | 0 | 0 | 0 | 0 | 0 | 0 | 21 |

The table shows the influence of a factor in the composition of the primary component. The sum of 0.25 is chosen as the breakoff point since $0.05 \times 5 = 0.25$. The factor of 0.25 was chosen through a reasoning like the Bonferroni correction, in that the sum is used to ensure that a false positive would not be chosen.

It could be seen that using the said analysis, the most significant factors are cement, coarse and fine natural aggregates, coarse and fine recycled aggregates, water content, total unit weight, fly ash content, filler, and crumb rubber.

The reason for the almost zero water to binder ratio is that the water to binder ratio is the ratio between the water over the binders that exist. The value of adding the water to binder ratio could be supplanted by adding the water content

and content of the binders into the model.

It should be considered however, that the variance of the other factors may not be considered significant under PCA since they are rightfully declared to be zero for most of the samples used. This shows why PCA would not be used.

Table 5.1-6 Breakdown using primary component analysis for DT only.

| Labels | PC1 | PC2 | PC3 |
|---|---|---|---|
| Cement (kg/m^3) | 0.1109 | 0.0203 | 0.5531 |
| Coarse aggregates (kg/m^3) | -0.6238 | 0.1808 | 0.3061 |
| Fine aggregates (kg/m^3) | 0.0013 | 0.5792 | -0.4791 |
| Coarse RCA (kg/m^3) | 0.7332 | -0.0878 | 0.0142 |
| Fine RCA (kg/m^3) | 0 | 0 | 0 |
| Water content (kg/m^3) | 0.0551 | -0.0015 | 0.2681 |
| Water to binder ratio | 0 | -0.0001 | 0.0002 |
| Total Unit Weight (kg/m^3) | 0.2325 | 0.7807 | 0.3372 |
| Granite Fines (kg/m^3) | 0 | 0 | 0 |
| Fly ash content (kg/m^3) | -0.0103 | 0.0238 | -0.0906 |
| Ground Granulated Blast Furnace Slag (GGBS) (kg/m^3) | 0 | 0 | 0 |
| Nano Silica (kg/m^3) | -0.0011 | 0.0028 | -0.0077 |
| Filler (kg/m^3) | -0.0304 | 0.0774 | -0.2135 |
| Crumb Rubber (kg/m^3) | -0.0525 | 0.0879 | -0.3605 |

| | | | |
|---|---|---|---|
| Metakaolinite Content (kg/m^3) | 0 | 0 | 0 |
| polypropylene fibre (% by volume) | 0.0001 | 0 | 0.0001 |
| dry curing | 0.0003 | 0.0001 | 0.001 |
| Superplasticizer (%) | 0.0002 | 0.0001 | 0.0009 |
| (Schmidt) Rebound number | 0 | 0 | 0 |
| UPV (km/s) | 0 | 0 | 0 |
| Age of concrete (days) | 0.0077 | -0.0077 | 0.0356 |
| Compressive strength (MPa) | | | |

Table 5.1-7 The values showing the sum of the multiplier applied to the principal components. The values in green are those whose sum is greater than 0.25

| Absolute value of Primary Components | PC1 | PC2 | PC3 | Sum | Rank of sums |
|---|---|---|---|---|---|
| Cement (kg/m^3) | 0.1109 | 0.0203 | 0.5531 | 0.6843 | 5 |
| Coarse aggregates (kg/m^3) | 0.6238 | 0.1808 | 0.3061 | 1.1107 | 2 |
| Fine aggregates (kg/m^3) | 0.0013 | 0.5792 | 0.4791 | 1.0596 | 3 |
| Coarse RCA (kg/m^3) | 0.7332 | 0.0878 | 0.0142 | 0.8352 | 4 |
| Fine RCA (kg/m^3) | 0 | 0 | 0 | 0 | 19 |
| Water content (kg/m^3) | 0.0551 | 0.0015 | 0.2681 | 0.3247 | 7 |
| Water to binder ratio | 0 | 0.0001 | 0.0002 | 0.0003 | 14 |
| Total Unit Weight (kg/m^3) | 0.2325 | 0.7807 | 0.3372 | 1.3504 | 1 |
| Granite Fines (kg/m^3) | 0 | 0 | 0 | 0 | 19 |

| | | | | | |
|---|---|---|---|---|---|
| Fly ash content (kg/m^3) | 0.0103 | 0.0238 | 0.0906 | 0.1247 | 9 |
| Ground Granulated Blast Furnace Slag (GGBS) (kg/m^3) | 0 | 0 | 0 | 0 | 19 |
| Nano Silica (kg/m^3) | 0.0011 | 0.0028 | 0.0077 | 0.0116 | 11 |
| Filler (kg/m^3) | 0.0304 | 0.0774 | 0.2135 | 0.3213 | 8 |
| Crumb Rubber (kg/m^3) | 0.0525 | 0.0879 | 0.3605 | 0.5009 | 6 |
| Metakaolinite Content (kg/m^3) | 0 | 0 | 0 | 0 | 19 |
| polypropylene fibre (% by volume) | 0.0001 | 0 | 0.0001 | 0.0002 | 15 |
| dry curing | 0.0003 | 0.0001 | 0.001 | 0.0014 | 12 |
| Superplasticizer (%) | 0.0002 | 0.0001 | 0.0009 | 0.0012 | 13 |
| (Schmidt) Rebound number | 0 | 0 | 0 | 0 | 19 |
| UPV (km/s) | 0 | 0 | 0 | 0 | 19 |
| Age of concrete (days) | 0.0077 | 0.0077 | 0.0356 | 0.051 | 10 |
| Compressive strength (MPa) | 0 | 0 | 0 | 0 | 19 |

It could be seen that using the said analysis, the most significant factors are cement, coarse and fine natural aggregates, coarse recycled aggregates, water content, total unit weight, fly ash content, filler, and crumb rubber. The only difference could be attributed to the fact that the DT dataset does not have fine aggregates.

## V.2 Analysis of Non-destructive Factors

### *V.2.1 Linear Regression*

Linear regression is used here since it is the most intuitive method by which a data analysis could be understood. Linear regression is of form $y=\beta_0+\sum_{i=1}^{n}\beta_i x_i$, which makes it very intuitive to understand and use.

Table 5.2-8 Result using linear regression

| | Estimate | SE | tStat | pValue |
|---|---|---|---|---|
| (Intercept) | -60.221 | 8.0389 | -7.4912 | 1.20E-12 |
| Cementkgm3 | -0.1468 | 0.0292 | -5.0212 | 9.82E-07 |
| CoarseAggregateskgm3 | -0.1855 | 0.0286 | -6.476 | 5.02E-10 |
| FineAggregateskgm3 | -0.1895 | 0.0287 | -6.6062 | 2.39E-10 |
| CoarseRCAkgm3 | -0.1859 | 0.0287 | -6.4848 | 4.77E-10 |
| FineRCAkgm3 | -0.1874 | 0.0287 | -6.5302 | 3.69E-10 |
| WaterContentkgm3 | -0.1374 | 0.0354 | -3.8827 | 0.00013 |
| WaterToBinderRatio | 12.98 | 6.4561 | 2.0106 | 0.04545 |
| TotalUnitWeightkgm3 | 0.1899 | 0.028 | 6.625 | 2.14E- |

| | | | | |
|---|---|---|---|---|
| | | 7 | 1 | 10 |
| GraniteFineskgm3 | -0.1958 | 0.0294 | -6.6597 | 1.76E-10 |
| FlyAshContentkgm3 | -0.1731 | 0.0301 | -5.7493 | 2.62E-08 |
| GroundGranulatedBlastFurnace Slag GGBSkgm3 | -0.2173 | 0.0322 | -6.7448 | 1.07E-10 |
| NanoSilicakgm3 | 0.1069 | 0.1511 | 0.7072 | 0.4801 |
| Fillerkgm3 | 0.1614 | 0.0288 | 5.6106 | 5.37E-08 |
| CrumbRubberkgm3 | -0.0704 | 0.014 | -5.0427 | 8.87E-07 |
| MetakaoliniteContentkgm3 | -0.2202 | 0.0312 | -7.0588 | 1.68E-11 |
| polypropyleneFibreByVolume | 0 | 0 | NaN | NaN |
| dryCuring | 0 | 0 | NaN | NaN |
| Superplasticizer | 13.063 | 1.6571 | 7.8828 | 1.01E-13 |
| SchmidtReboundNumber | 0.8024 | 0.055 | 14.58 | 3.41E-35 |
| UPVkms | 7.1543 | 1.07 | 6.686 | 1.51E-10 |
| AgeOfConcretedays | -0.0087 | 0.0074 | -1.1639 | 0.24558 |

The estimate shows what the coefficient that would be attached to the factor would be. The standard error shows the variability of a coefficient. In order words, it shows how far apart the value that would have been predicted by regression from the other values. tStat is the estimate over the standard

error. The pValue is the probability of the coefficient being insignificant, with 0.05 being the p value that is the threshold whether the value would be removed. The result from the linear regression shows the importance of each of the variables and coefficient that they would add to the model.

Most notably, it could be seen that water to binder ratio, nano silica weight per volume of concrete, and the age of concrete is not significant.

It could also be seen that polypropylene Fiber by Volume, whether the concrete is dry cured or not are not factors in the dataset. This is because these factors would have been included in the other split of the data. The other split of the data would not contain any non-destructive testing methods.

We know however through numerous studies that the age of concrete matters. This paradox could be explained by other factors such the Schmidt rebound number and ultrasonic pulse velocity as being able to relay the same information with regards to the state of the concrete, on the matter of its compressive strength.

Table 5.2-9 Model training results

| | |
|---|---|
| RMSE (Validation) | 2.7205 |
| R-Squared (Validation) | 0.95 |
| MSE (Validation) | 7.4013 |
| MAE (Validation) | 2.0017 |
| Prediction speed | ~8600 obs/sec |
| Training time | 11.203 sec |

Table 5.2-10 Model parameters

| Model Type | |
|---|---|
| Preset | Linear |
| Terms | Linear |
| Robust option | Off |

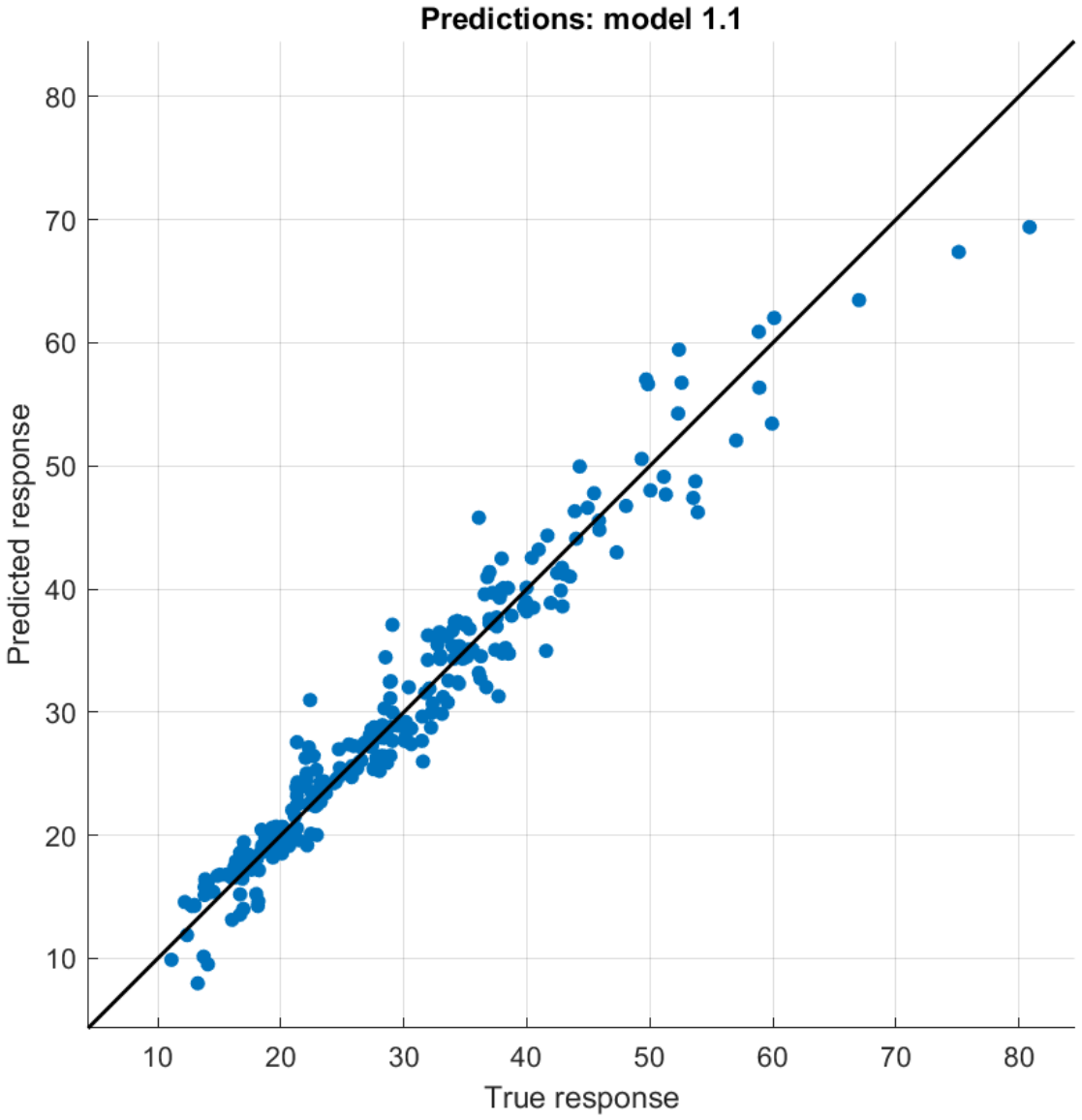



Figure 5.2.6 True vs Predicted for Linear Regression

The true vs predicted response graph shows the how much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also shows that there are outliers and that most of the reliable

data is between 10 to 45 MPa compressive strength.

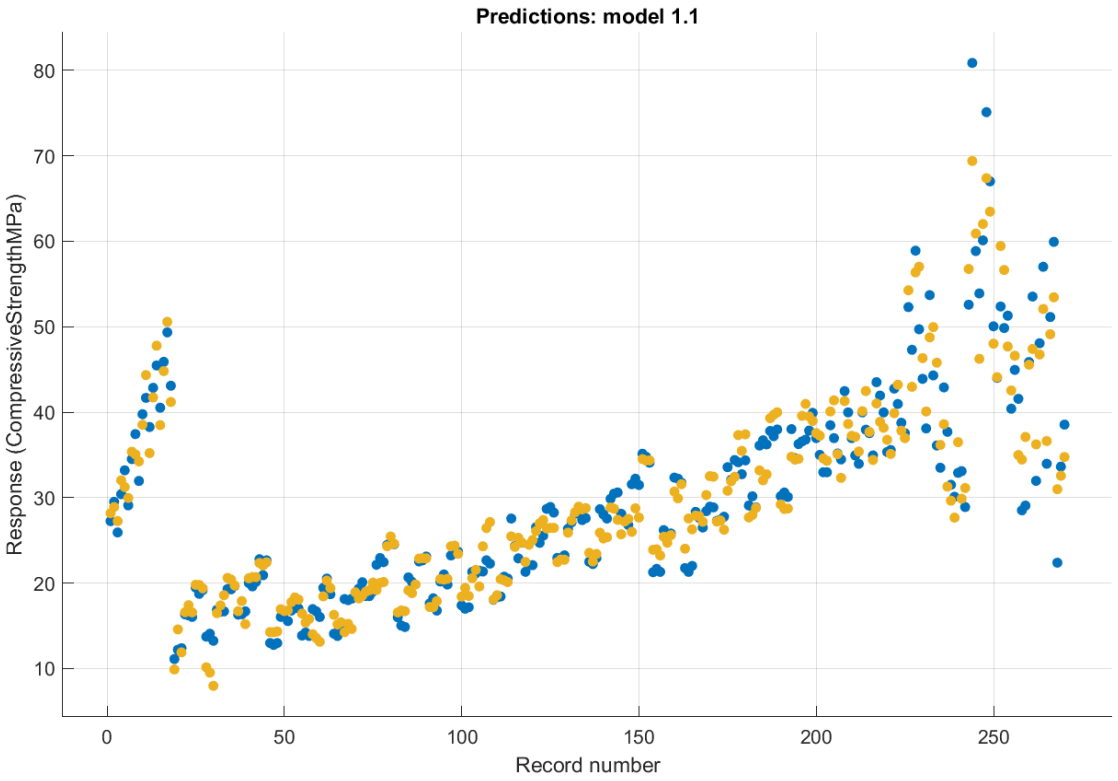



Figure 5.2.7 Response Plot for Linear Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

### *V.2.2 Stepwise Quadratic Regression with Interactions*

This part has been added to give another method by which the neural network method should be able to beat.

Table 5.2-11 Result by Stepwise Quadratic Regression with Interactions

| | Estimate | SE | tStat | pValue |
|---|---|---|---|---|
| (Intercept) | 42.564 | 17.324 | 2.4569 | 0.01471 |
| Cementkgm3 | -0.204 | 0.02026 | -10.07 | 3.49E-20 |
| CoarseAggregateskgm3 | -0.15382 | 0.01442 | -10.666 | 4.58E-22 |
| FineAggregateskgm3 | -0.17503 | 0.01459 | -11.994 | 2.21E-26 |
| CoarseRCAkgm3 | -0.17596 | 0.01506 | -11.686 | 2.29E-25 |
| FineRCAkgm3 | -0.17481 | 0.01541 | -11.346 | 2.95E-24 |
| WaterToBinderRatio | -129.25 | 13.031 | -9.9192 | 1.03E-19 |
| TotalUnitWeightkgm3 | 0.15722 | 0.01624 | 9.6802 | 5.64E-19 |
| GraniteFineskgm3 | -0.18007 | 0.01567 | -11.49 | 1.00E-24 |
| FlyAshContentkgm3 | -0.17954 | 0.02016 | -8.904 | 1.24E-16 |
| GroundGranulatedBlastFurnaceSlagGGBSkgm3 | -0.15427 | 0.02065 | -7.4725 | 1.39E-12 |
| NanoSilicakgm3 | 565.88 | 114.13 | 4.9583 | 1.33E-06 |

| | | | | |
|---|---|---|---|---|
| Fillerkgm3 | 0.088931 | 0.02007 | 4.4311 | 1.41E-05 |
| CrumbRubberkgm3 | -0.06443 | 0.00804 | -8.009 | 4.68E-14 |
| MetakaoliniteContentkgm3 | -0.19062 | 0.01996 | -9.5524 | 1.39E-18 |
| SchmidtReboundNumber | -0.21377 | 0.16284 | -1.3127 | 1.91E-01 |
| UPVkms | -1.6921 | 4.1377 | -0.409 | 0.68293 |
| AgeOfConcretedays | 0.36197 | 0.06547 | 5.529 | 8.23E-08 |
| CoarseAggregateskgm3 : TotalUnitWeightkgm3 | -1.12E-05 | 3.10E-06 | -3.6044 | 3.79E-04 |
| CoarseAggregateskgm3 : NanoSilicakgm3 | -0.67958 | 0.1371 | -4.9566 | 1.34E-06 |
| TotalUnitWeightkgm3: UPVkms | 0.005257 | 0.00197 | 2.6746 | 7.99E-03 |
| UPVkms: AgeOfConcretedays | -0.05779 | 0.01606 | -3.598 | 0.00039 |
| WaterToBinderRatio^2 | 71.851 | 9.5063 | 7.5582 | 8.15E-13 |
| SchmidtReboundNumber^2 | 0.015259 | 0.00246 | 6.2105 | 2.25E-09 |
| AgeOfConcretedays^2 | -0.00093 | 0.00027 | -3.4098 | 0.00076 |

The estimate shows what the coefficient that would be attached to the factor would be. The standard error shows the variability of a coefficient. In order words, it shows how far apart the value that would have been predicted by regression

from the other values. tStat is the estimate over the standard error. The pValue is the probability of the coefficient being insignificant, with 0.05 being the p value that is the threshold whether the value would be removed.

The result from the table shows the different coefficients and the result that they add to the model. A feature labeled as $A:B$ would add an interaction term $\beta_{AB}x_A x_B$ to the standard linear equation. In other words, $A:B$ is an interaction term between A and B.

Table 5.2-12 Model training results

| | |
|---|---|
| RMSE (Validation) | 2.9804 |
| R-Squared (Validation) | 0.94 |
| MSE (Validation) | 8.8826 |
| MAE (Validation) | 1.8726 |
| Prediction speed | ~6500 obs/sec |
| Training time | 320.71 sec |

Table 5.2-13 Model parameters

| Model Type | |
|---|---|
| Preset | Stepwise Linear |
| Initial terms | Linear |
| Upper bound on terms | Quadratic |
| Maximum number of steps | 1000 |

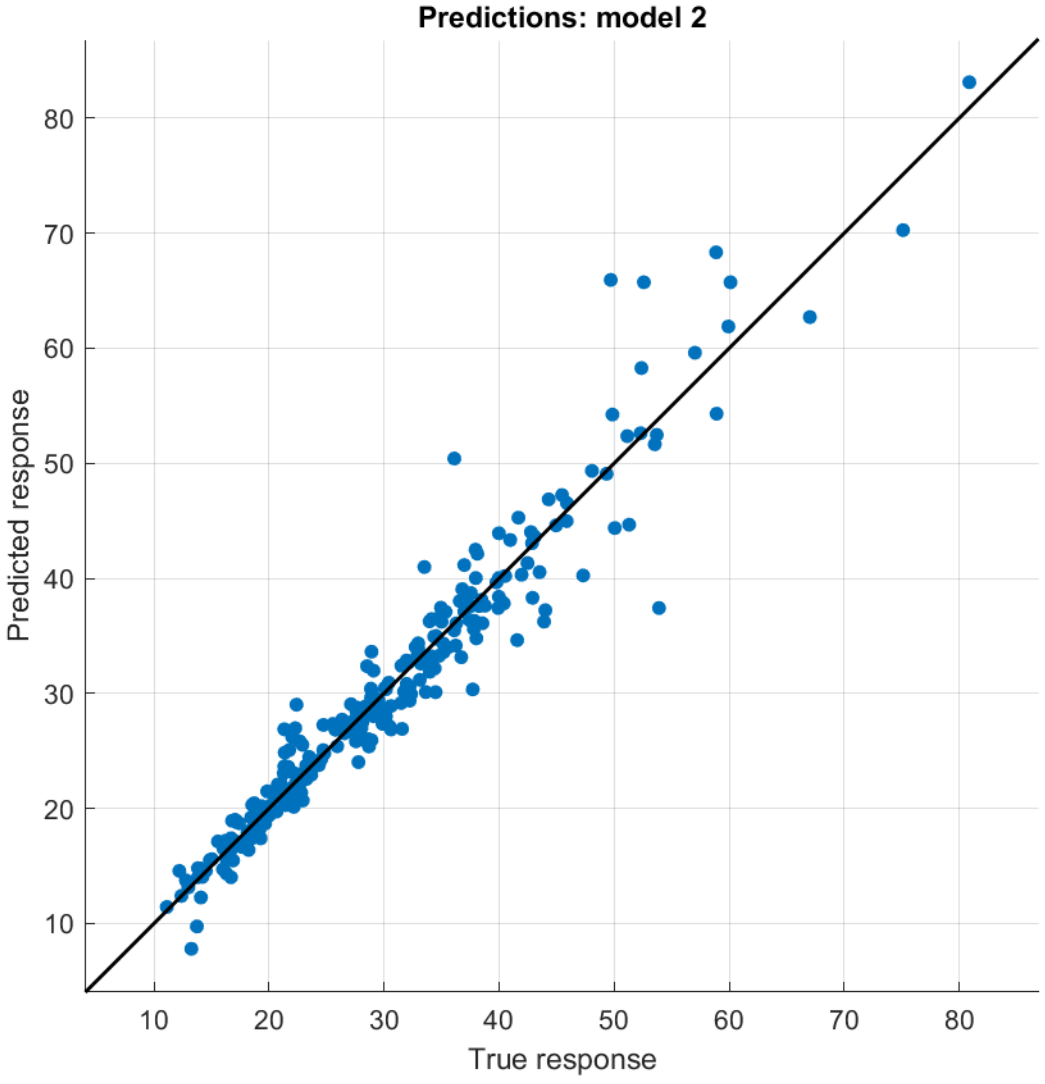


Figure 5.2.8 Predicted vs Actual for Stepwise Regression

The true vs predicted response graph shows the how much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also shows that there are outliers and that most of the reliable data is between 10 to 45 MPa compressive strength.

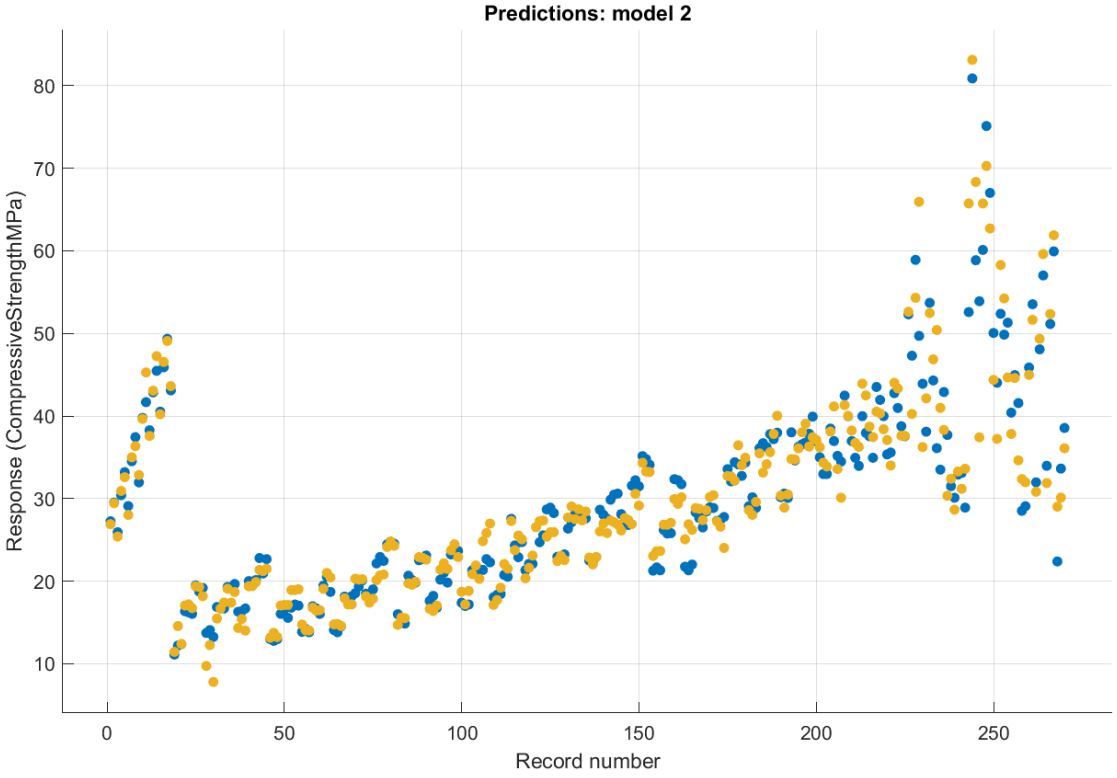



Figure 5.2.9 Response Plot for Stepwise Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed

that the results to an extent match up to the true values.

### *V.2.3Exponential Gaussian Process Regression*

This part has been added to give another method by which the neural network method should be able to beat.

Table 5.2-14 Model training results

| | |
|---|---|
| RMSE (Validation) | 2.2208 |
| R-Squared (Validation) | 0.96 |
| MSE (Validation) | 4.9318 |
| MAE (Validation) | 1.3123 |
| Prediction speed | ~12000 obs/sec |
| Training time | 0.97213 sec |

Table 5.2-15 Model parameters

| | |
|---|---|
| Model Type | |
| Preset | Exponential GPR |
| Basis function | Constant |
| Kernel function | Exponential |
| Use isotropic kernel | true |
| Kernel scale | Automatic |
| Signal standard deviation | Automatic |
| Sigma | Automatic |
| Standardize | true |
| Optimize numeric parameters | true |

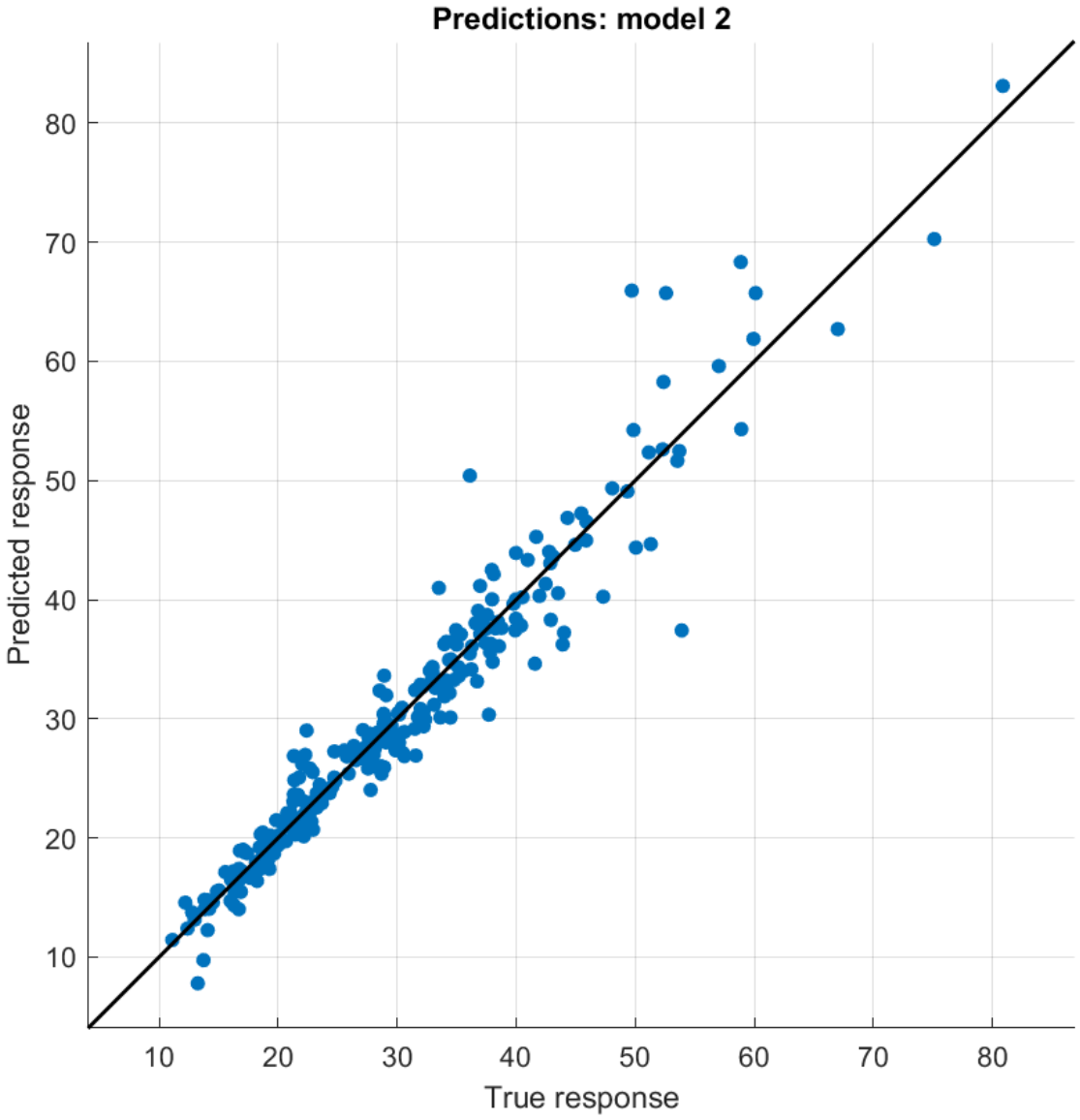



Figure 5.2.10 Predicted vs Actual for Exponential Gaussian Process Regression

The true vs predicted response graph shows the how much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also

shows that there are outliers and that most of the reliable data is between 10 to 45 MPa compressive strength.

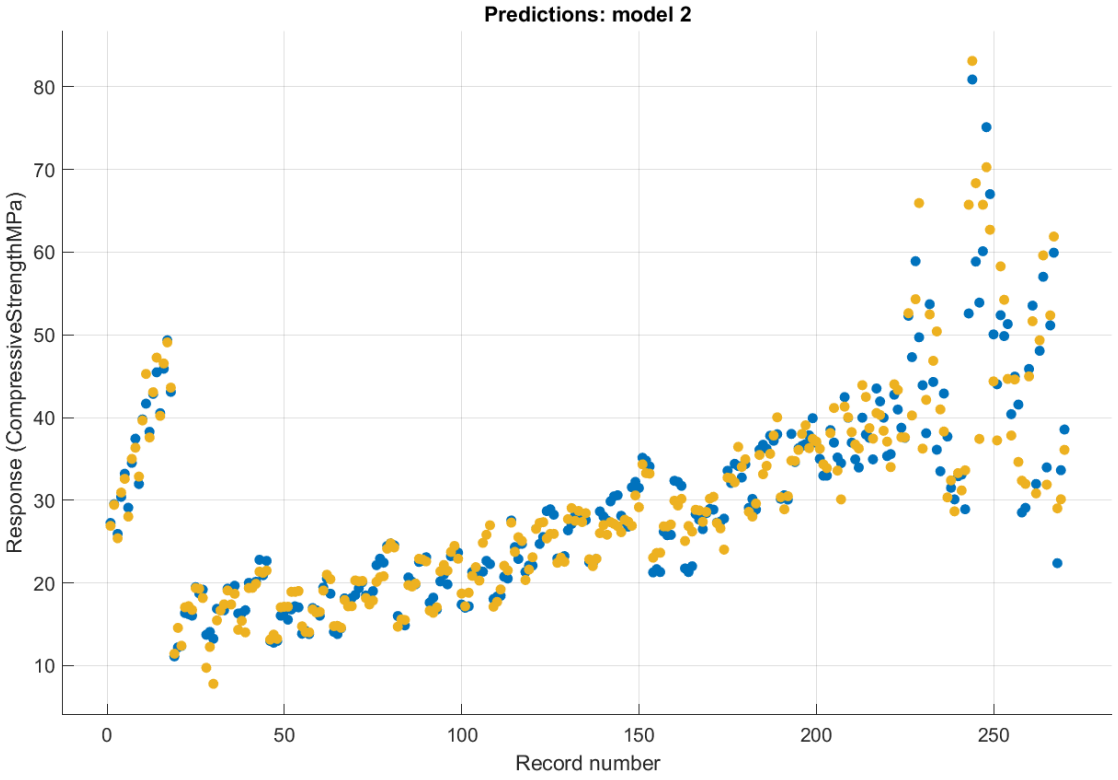



Figure 5.2.11 Response Plot for Exponential Gaussian Process Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

### *V.2.4 Untweaked neural network*

Table 5.2-16 Model training results

| | |
|---|---|
| RMSE (Validation) | 3.0513 |
| R-Squared (Validation) | 0.93 |
| MSE (Validation) | 9.3106 |
| MAE (Validation) | 1.7819 |
| Prediction speed | ~18000 obs/sec |
| Training time | 3.1385 sec |

Table 5.2-17 Model parameters

| Model Type | |
|---|---|
| Preset | Bilayered Neural Network |
| Number of fully connected layers | 2 |
| First layer size | 10 |
| Second layer size | 10 |
| Activation | ReLU |
| Iteration limit | 1000 |
| Regularization strength (Lambda) | 0 |
| Standardize data | Yes |

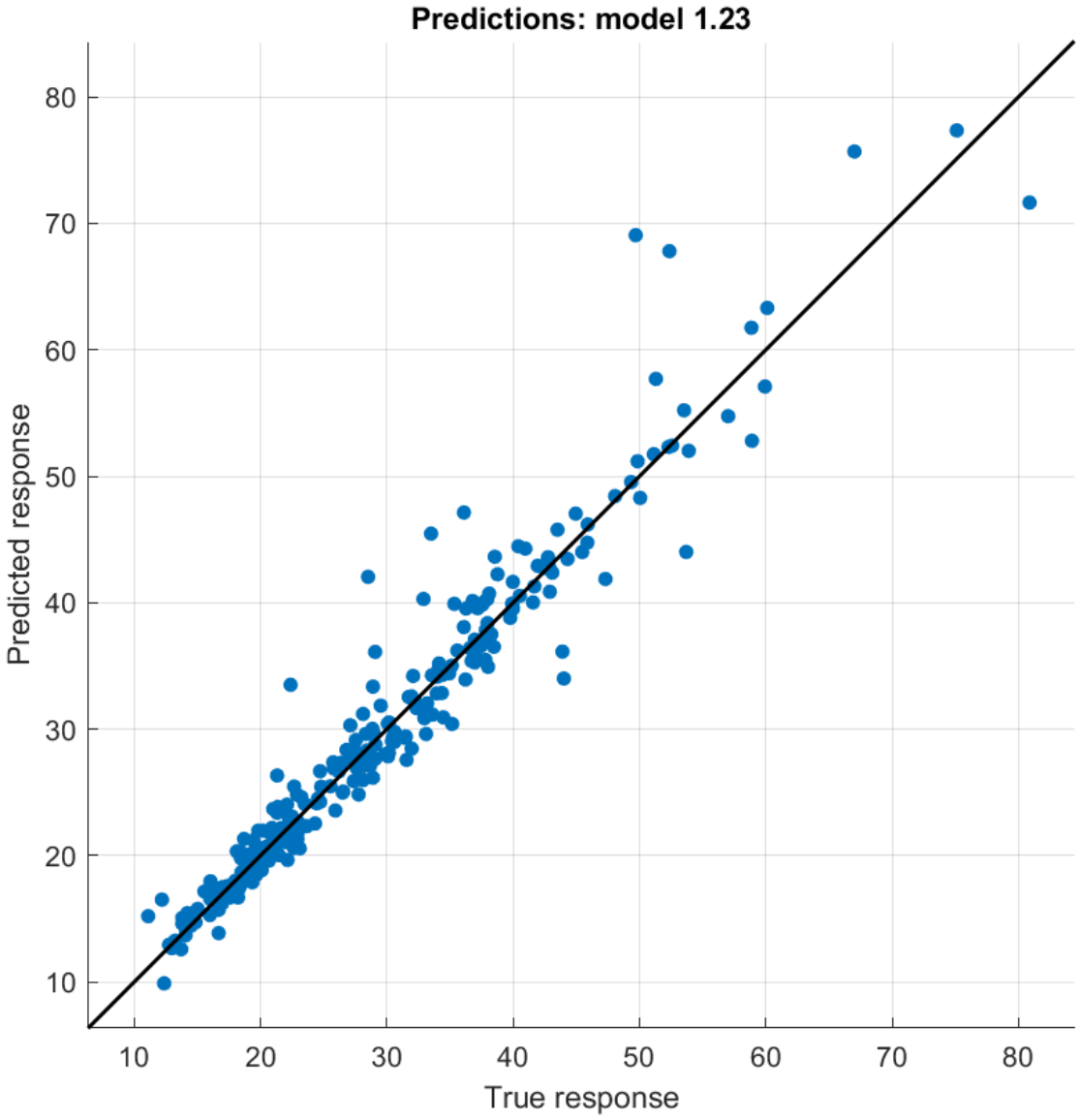



Figure 5.2.12 Predicted vs Actual for Untweaked Neural Network

The true vs predicted response graph shows the how much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also shows that there are outliers and that most of the reliable

data is between 10 to 45 MPa compressive strength.

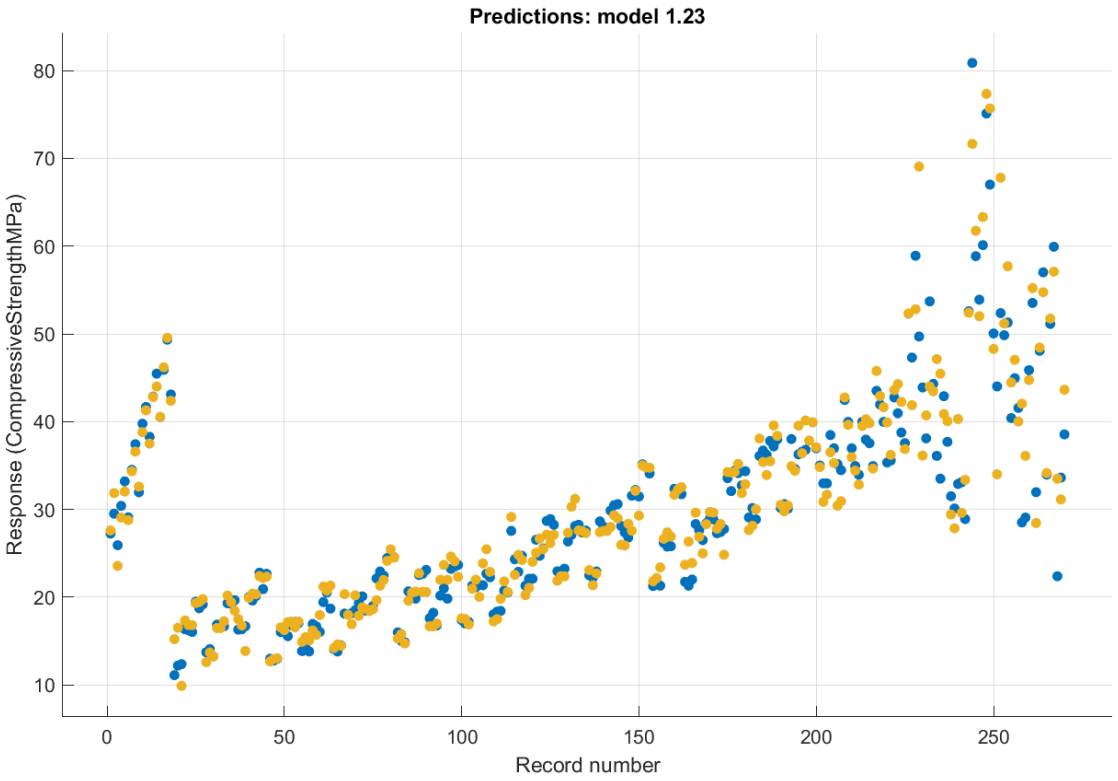



Figure 5.2.13 Response Plot for Untweaked Neural Network

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

### *V.2.5 Tweaked neural network*

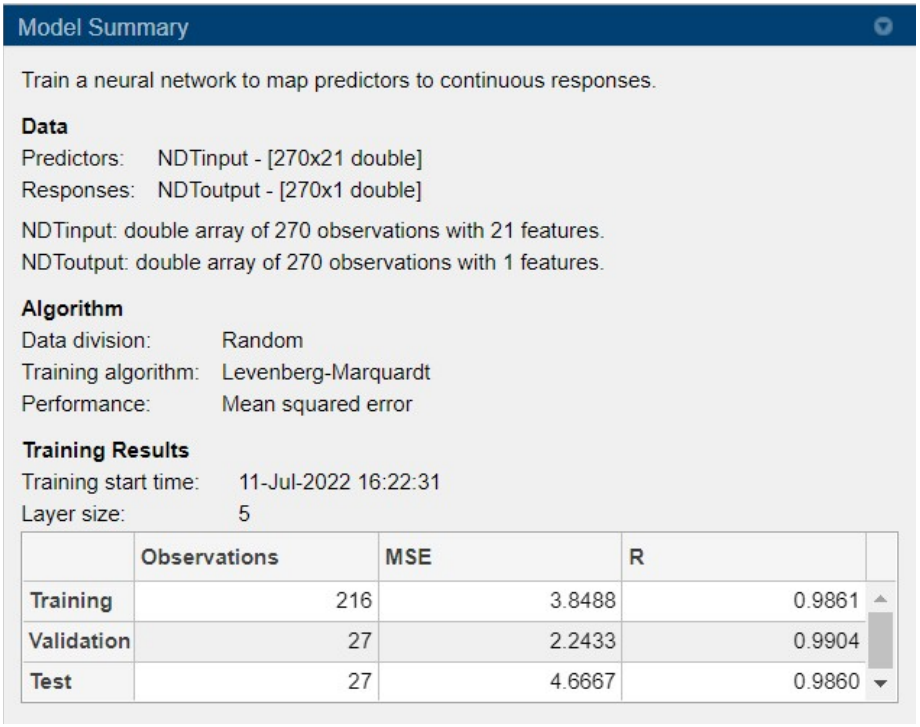

Model Summary
Train a neural network to map predictors to continuous responses.
Data
Predictors: NDTinput - [270x21 double]
Responses: NDToutput - [270x1 double]
NDTinput: double array of 270 observations with 21 features.
NDToutput: double array of 270 observations with 1 features.
Algorithm
Data division: Random
Training algorithm: Levenberg-Marquardt
Performance: Mean squared error
Training Results
Training start time: 11-Jul-2022 16:22:31
Layer size: 5
Observations MSE R
Training 216 3.8488 0.9861
Validation 27 2.2433 0.9904
Test 27 4.6667 0.9860

Figure 5.2.14 Model Summary.

The Figure above shows the summary of the model. The R value shown indicates that the model created is a good match to the data given. Moreover, the closeness of the mean square error between training, validation and test means that no overfitting has occurred. The test-train ratio of 80:20 is also implemented. This result is chosen since the mean squared error is lower than the value obtained using other methods, such as stepwise regression.

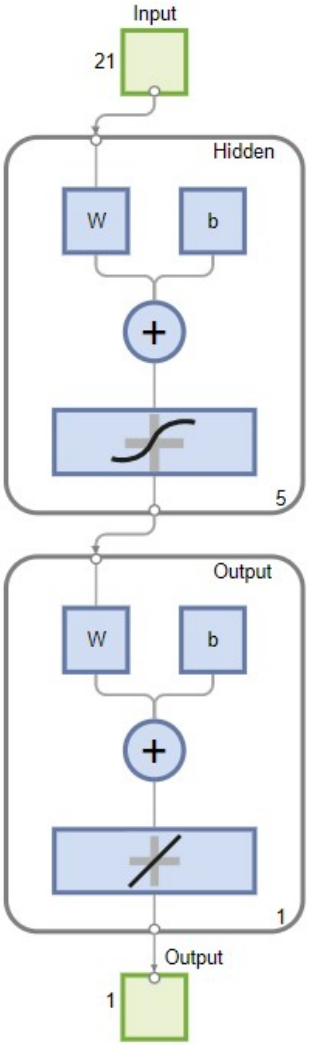



Figure 5.2.15 Diagram of the neural network.

The Figure above shows that a sigmoid activation is used. It also shows that there are twenty-one features as input and one as output. It also shows that the hidden layer has a size of five.

**Training Results**

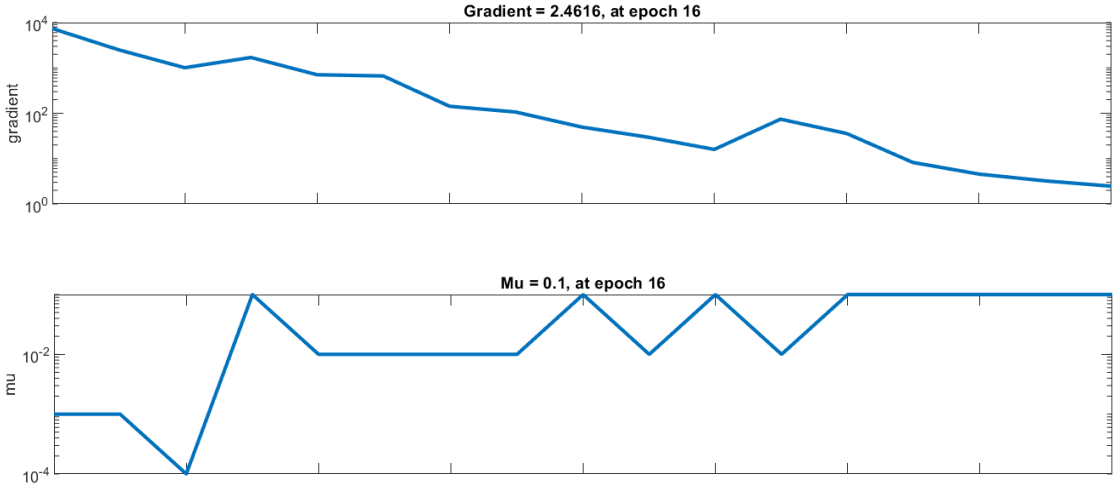
Training finished: Met validation criterion

**Training Progress**

| Unit | Initial Value | Stopped Value | Target Value |
|---|---|---|---|
| Epoch | 0 | 16 | 1000 |
| Elapsed Time | - | 00:00:00 | - |
| Performance | 1.78e+03 | 2.26 | 0 |
| Gradient | 7.39e+03 | 2.46 | 1e-07 |
| Mu | 0.001 | 0.1 | 1e+10 |
| Validation Checks | 0 | 6 | 6 |

Figure 5.2.16 Training progress with elapsed time and different stopping criteria

The Figure above shows that the machine learning run is successful. Namely, the mean squared error has decreased. This is shown under performance. The training was finished by meeting the validation criteria, which is that for six consecutive iterations, the validation error increases.



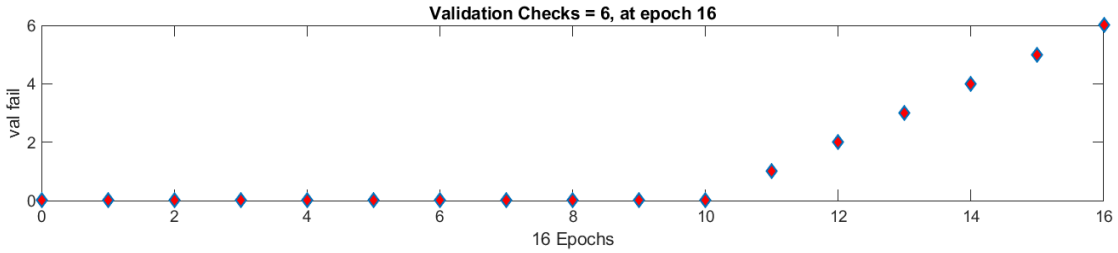



Figure 5.2.17 Different charts showing the various training parameters.

The gradient chart shows that the steps needed to reach the goal gets smaller, which is the expected outcome.

The mu chart measures how near to the newton's method the analysis would be. A high mu would create the algorithm be equivalent to gradient descent with little steps, whereas a small mu would create the algorithm be nearer to newton's method. it is useful to induce to Newton's method as quickly as attainable since it is quicker and is more accurate close to an error minimum. Thus, mu is shrunken after every successful step (reduction in performance function) and is augmented only if a tentative step would increase the performance function. in this approach, the performance function is always reduced at every iteration of the algorithm.

The validation checks show the accumulated amount of validation checks failed in a row. The chart looks as expected

since the six failures of each epoch to increase the performance on the validation test caused the test to be finished.

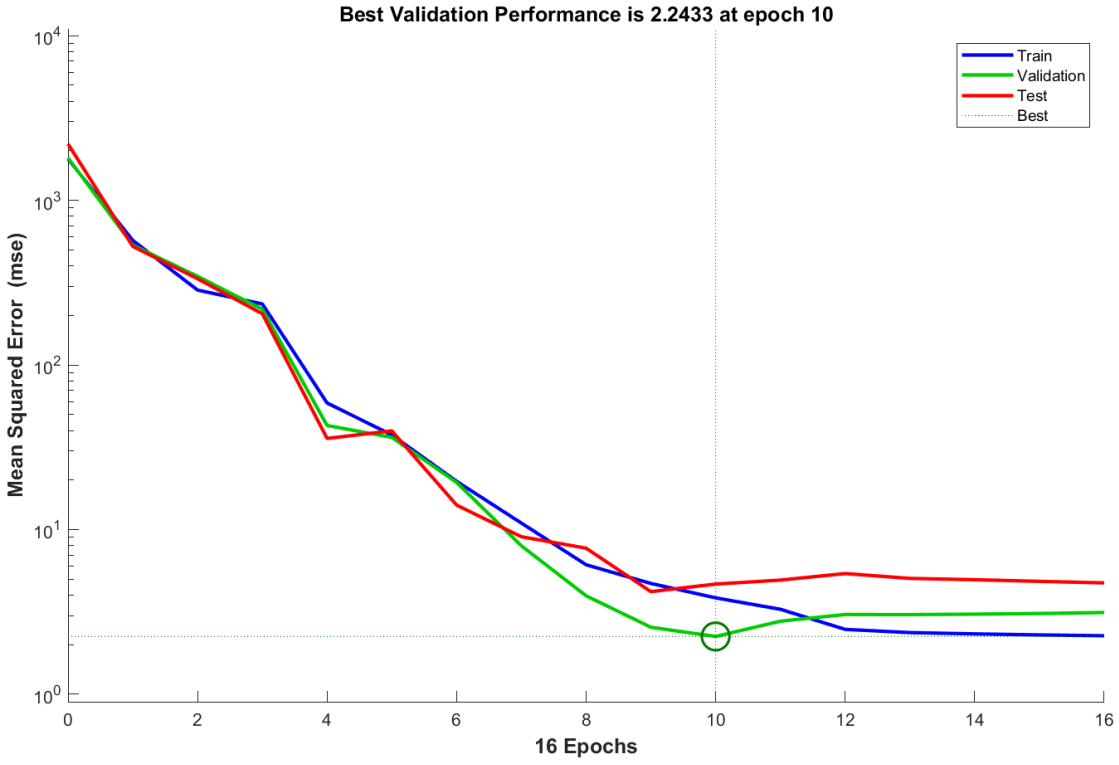



Figure 5.2.18 Performance (Mean squared error) for each of the epochs or train, validation, and test.

The Figure above shows that the neural network is improving. I also show that the best version of the neural network was found on epoch ten.

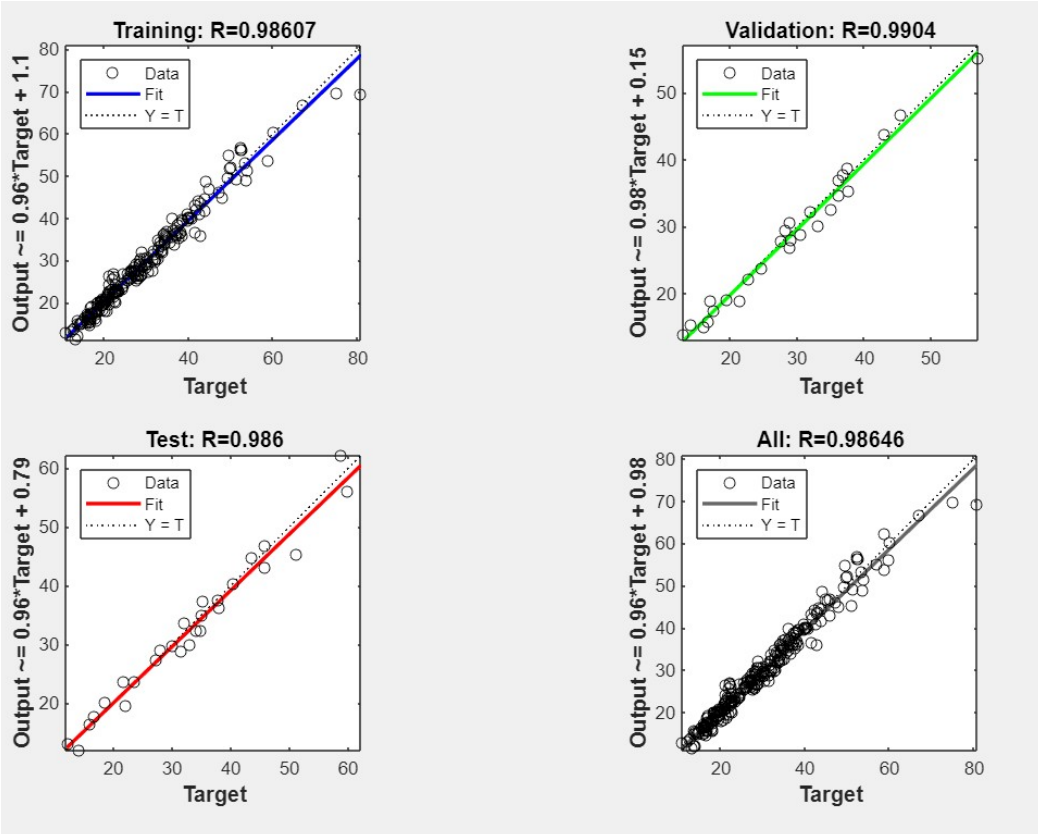



Figure 5.2.19 Charts showing the correlation between the target and the output.

The Figure above shows that the neural network is predicting well. Moreover, it demonstrates that there is much alignment between the output of the neural network and the target value.

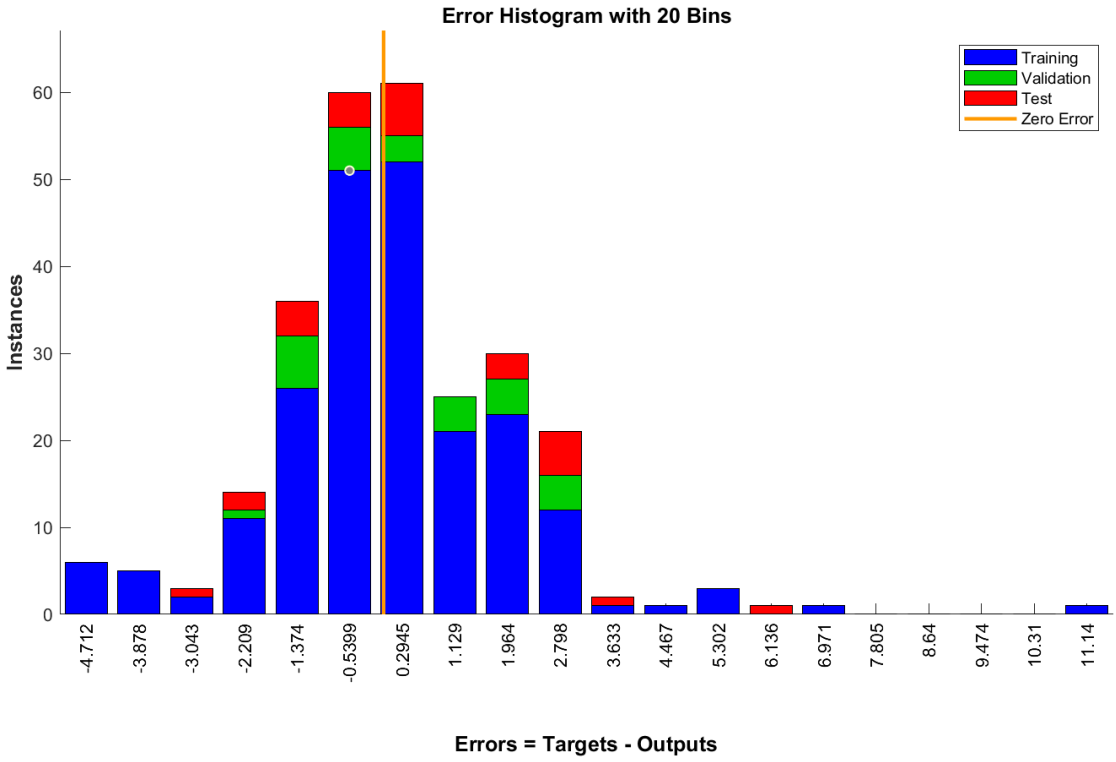



Figure 5.2.20 Error histogram of the neural network.

The error histogram mostly follows the curve expected from the neural network, namely that except for outliers, the errors follow the normal distribution. Nevertheless, the outliers show the blind spots of the model.

### V.2.5.1 Comparison between predicted values vs real values

The comparison of predicted values vs real values is used to see to what extent the predictions will align with the real data. The comparison is as follows:

Table 5.2-18 Comparison between real and predicted values when the neural network is applied to the original dataset.

| Compressive Strength (Source) | Compressive Strength (Predicted) |
|---:|---:|
| 27.25 | 27.10 |
| 29.52 | 30.54 |
| 25.93 | 26.11 |
| 30.41 | 30.80 |
| 33.2 | 33.33 |
| 29.1 | 28.66 |
| 34.52 | 33.79 |
| 37.44 | 36.78 |
| 31.96 | 32.14 |
| 39.77 | 39.50 |
| 41.68 | 43.19 |
| 38.27 | 36.70 |
| 42.86 | 43.55 |
| 45.47 | 46.61 |
| 40.53 | 40.22 |
| 45.9 | 46.79 |
| 49.34 | 49.57 |
| 43.1 | 43.76 |
| 11.117673 | 12.87 |
| 12.207564 | 13.13 |
| 12.382182 | 13.08 |
| 16.35327 | 17.06 |
| 16.229664 | 17.22 |
| 16.044255 | 16.80 |
| 19.489527 | 20.12 |
| 18.747891 | 20.12 |
| 19.183455 | 20.09 |
| 13.734 | 12.07 |
| 14.082255 | 12.02 |
| 13.254291 | 11.48 |
| 16.8732 | 15.59 |

| | |
|---:|---:|
| 16.655418 | 16.00 |
| 16.698582 | 16.74 |
| 19.314909 | 20.34 |
| 19.270764 | 20.16 |
| 19.663164 | 19.62 |
| 16.311087 | 15.21 |
| 16.35327 | 16.46 |
| 16.698582 | 14.75 |
| 20.0124 | 20.17 |
| 19.62 | 20.40 |
| 20.142873 | 20.28 |
| 22.802364 | 22.17 |
| 20.927673 | 22.13 |
| 22.671891 | 22.33 |
| 12.992364 | 13.82 |
| 12.774582 | 13.67 |
| 12.98844 | 13.87 |
| 16.044255 | 16.42 |
| 16.568109 | 16.42 |
| 15.565527 | 16.50 |
| 16.792758 | 18.87 |
| 17.178291 | 19.16 |
| 17.047818 | 18.87 |
| 13.864473 | 15.67 |
| 14.213709 | 15.10 |
| 13.821309 | 14.92 |
| 16.960509 | 16.01 |
| 16.698582 | 15.79 |
| 16.044255 | 15.63 |
| 19.445382 | 18.98 |
| 20.535273 | 20.17 |
| 18.704727 | 19.51 |
| 14.082255 | 15.34 |
| 13.821309 | 14.91 |
| 14.5188 | 14.97 |
| 18.137709 | 15.79 |
| 18.006255 | 16.21 |
| 18.180873 | 15.70 |
| 18.530109 | 20.03 |

| | |
|---:|---:|
| 19.358073 | 19.32 |
| 20.099709 | 19.65 |
| 18.485964 | 17.96 |
| 18.485964 | 18.15 |
| 19.009818 | 18.47 |
| 22.149018 | 19.61 |
| 22.933818 | 20.08 |
| 22.454109 | 20.31 |
| 24.459273 | 23.73 |
| 24.808509 | 24.67 |
| 24.546582 | 24.07 |
| 16.001091 | 14.95 |
| 15.03873 | 15.47 |
| 14.867055 | 15.41 |
| 20.666727 | 18.21 |
| 20.142873 | 18.02 |
| 19.837782 | 18.45 |
| 22.541418 | 22.80 |
| 22.671891 | 22.74 |
| 23.107455 | 22.71 |
| 17.61876 | 17.36 |
| 18.225018 | 17.36 |
| 16.785891 | 17.76 |
| 20.187018 | 20.82 |
| 21.014982 | 21.36 |
| 19.837782 | 20.82 |
| 23.238909 | 23.28 |
| 23.499855 | 23.59 |
| 23.674473 | 22.68 |
| 17.396073 | 17.21 |
| 17.003673 | 17.52 |
| 17.178291 | 17.29 |
| 21.320073 | 19.52 |
| 21.145455 | 20.94 |
| 21.451527 | 18.85 |
| 21.364218 | 24.16 |
| 22.671891 | 26.18 |
| 22.279491 | 26.94 |
| 18.0504 | 17.94 |

| | |
|---|---|
| 18.355491 | 18.52 |
| 18.4428 | 19.85 |
| 20.753055 | 21.37 |
| 20.535273 | 21.01 |
| 27.555309 | 27.87 |
| 24.3288 | 23.28 |
| 22.900464 | 24.30 |
| 24.7212 | 23.76 |
| 21.320073 | 20.71 |
| 22.10193 | 22.51 |
| 22.104873 | 23.26 |
| 26.552727 | 25.91 |
| 24.7212 | 26.84 |
| 25.549164 | 26.98 |
| 28.688364 | 26.61 |
| 28.907127 | 26.61 |
| 28.2528 | 26.61 |
| 22.9554 | 22.42 |
| 22.933818 | 22.93 |
| 23.2497 | 22.80 |
| 26.35947 | 27.25 |
| 27.118764 | 28.43 |
| 28.122327 | 28.96 |
| 28.2528 | 27.69 |
| 27.380691 | 27.25 |
| 27.598473 | 27.46 |
| 22.497273 | 22.40 |
| 22.236327 | 21.48 |
| 22.933818 | 22.40 |
| 28.6452 | 26.42 |
| 28.035018 | 25.92 |
| 27.555309 | 26.34 |
| 29.865564 | 28.85 |
| 30.476727 | 28.73 |
| 30.6072 | 27.49 |
| 28.122327 | 25.83 |
| 27.380691 | 26.68 |
| 26.813673 | 27.42 |
| 31.566618 | 27.54 |

| | |
|---|---|
| 32.219964 | 30.17 |
| 31.479309 | 28.88 |
| 35.141382 | 32.54 |
| 34.793127 | 32.32 |
| 34.094655 | 32.25 |
| 21.276909 | 22.70 |
| 21.669309 | 22.83 |
| 21.320073 | 22.09 |
| 26.203491 | 25.85 |
| 25.767927 | 25.35 |
| 25.811091 | 25.98 |
| 32.351418 | 30.50 |
| 32.219964 | 29.78 |
| 31.740255 | 31.41 |
| 21.756618 | 23.70 |
| 21.320073 | 26.40 |
| 22.017564 | 25.62 |
| 28.340109 | 29.46 |
| 27.642618 | 29.31 |
| 26.508582 | 27.75 |
| 28.427418 | 29.07 |
| 28.950291 | 30.55 |
| 28.862982 | 30.55 |
| 27.293382 | 27.73 |
| 27.423855 | 27.53 |
| 27.773091 | 25.33 |
| 33.571782 | 33.45 |
| 32.089491 | 33.63 |
| 34.400727 | 34.79 |
| 34.1388 | 36.02 |
| 32.743818 | 34.77 |
| 34.356582 | 36.31 |
| 29.080764 | 27.89 |
| 30.159864 | 28.41 |
| 28.862982 | 29.09 |
| 36.1008 | 35.62 |
| 36.710982 | 33.94 |
| 36.231273 | 34.61 |
| 37.800873 | 35.37 |

| | |
|---:|---:|
| 37.190691 | 35.90 |
| 37.975491 | 36.28 |
| 30.170655 | 29.88 |
| 30.6072 | 29.30 |
| 30.084327 | 29.30 |
| 38.018655 | 36.21 |
| 34.618509 | 35.79 |
| 36.275418 | 36.95 |
| 36.580509 | 37.20 |
| 36.798291 | 37.77 |
| 37.845018 | 37.58 |
| 39.92277992 | 40.99 |
| 36.96911197 | 37.10 |
| 35 | 35.00 |
| 32.97297297 | 30.58 |
| 32.97297297 | 29.88 |
| 38.47490347 | 36.01 |
| 36.96911197 | 36.32 |
| 35.17374517 | 35.26 |
| 34.47876448 | 34.26 |
| 42.47104247 | 44.16 |
| 39.98069498 | 39.95 |
| 36.96911197 | 37.17 |
| 34.94208494 | 35.54 |
| 33.95752896 | 32.65 |
| 39.98069498 | 40.24 |
| 37.95366795 | 38.87 |
| 37.54826255 | 38.37 |
| 34.94208494 | 36.94 |
| 43.51351351 | 44.76 |
| 41.94980695 | 42.18 |
| 39.98069498 | 39.99 |
| 35.34749035 | 37.36 |
| 35.57915058 | 34.21 |
| 42.76061776 | 41.01 |
| 40.96525097 | 39.92 |
| 38.76447876 | 39.53 |
| 37.54826255 | 38.75 |
| 52.30252596 | 56.35 |

| | |
|---|---|
| 47.3033537 | 46.15 |
| 58.90143334 | 53.73 |
| 49.70295638 | 54.83 |
| 43.90391656 | 41.73 |
| 38.10487674 | 39.09 |
| 53.70229419 | 49.00 |
| 44.30385034 | 48.69 |
| 36.10520784 | 39.96 |
| 33.50563827 | 34.22 |
| 42.90408211 | 35.96 |
| 37.70494296 | 35.30 |
| 31.50596936 | 30.09 |
| 30.10620113 | 29.68 |
| 32.90573759 | 32.63 |
| 33.10570448 | 30.15 |
| 28.90639979 | 26.84 |
| 52.58 | 56.34 |
| 80.87 | 69.31 |
| 58.86 | 62.20 |
| 53.9 | 51.44 |
| 60.11 | 60.33 |
| 75.11 | 69.77 |
| 67.01 | 66.79 |
| 50.05 | 52.14 |
| 44.02 | 44.64 |
| 52.37 | 56.80 |
| 49.85 | 51.87 |
| 51.3 | 49.29 |
| 40.41 | 40.24 |
| 44.95 | 46.85 |
| 41.57 | 36.62 |
| 28.52 | 29.89 |
| 29.08 | 32.14 |
| 45.87 | 43.02 |
| 53.53 | 53.18 |
| 31.97 | 32.23 |
| 48.07 | 44.94 |
| 57.02 | 55.16 |
| 33.97 | 32.02 |

| | |
|---|---|
| 51.14 | 45.31 |
| 59.93 | 56.03 |
| 22.39 | 26.73 |
| 33.63 | 32.17 |
| 38.55 | 39.75 |

It could be seen that there are some differences between the real value and the predicted value.

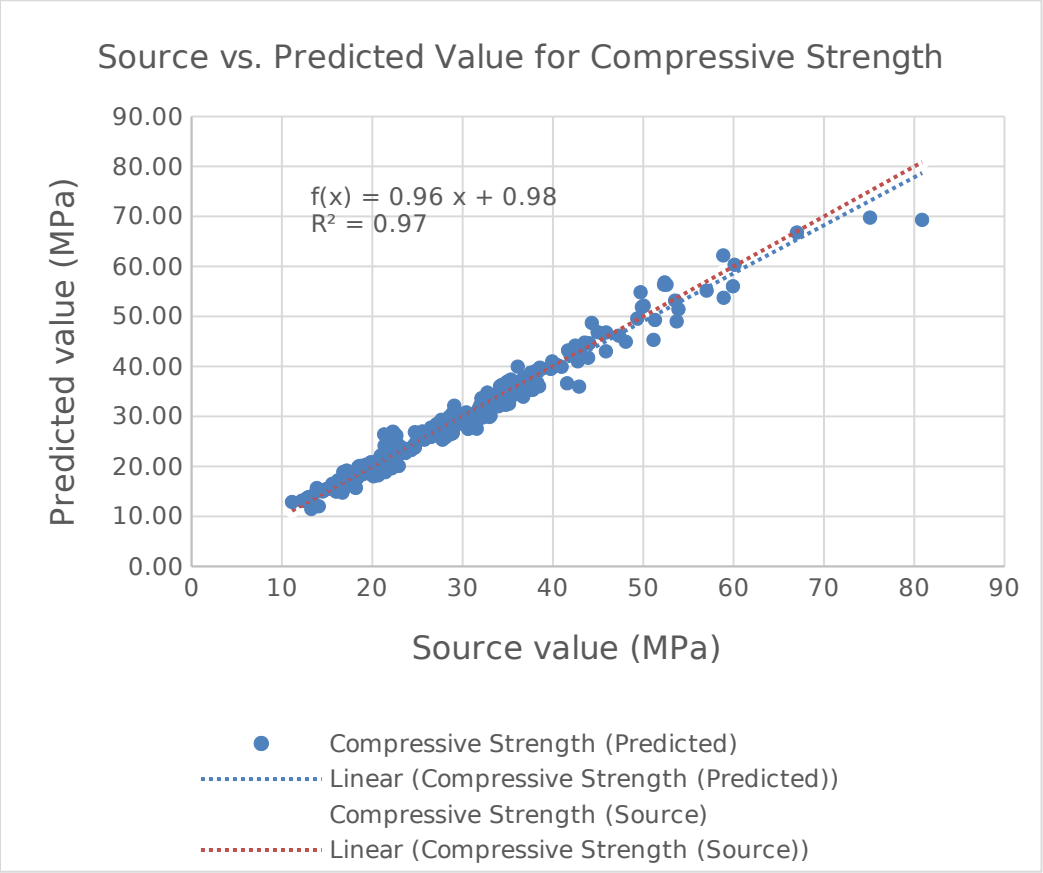



Figure 5.2.21 Source vs. Predicted Value for Compressive Strength

The chart would confirm the extent of similarity between the source value and the predicted value. The

comparison between the y=x trendline also highlights the difference between the real and predicted values. The graph also shows the areas where the outliers are.

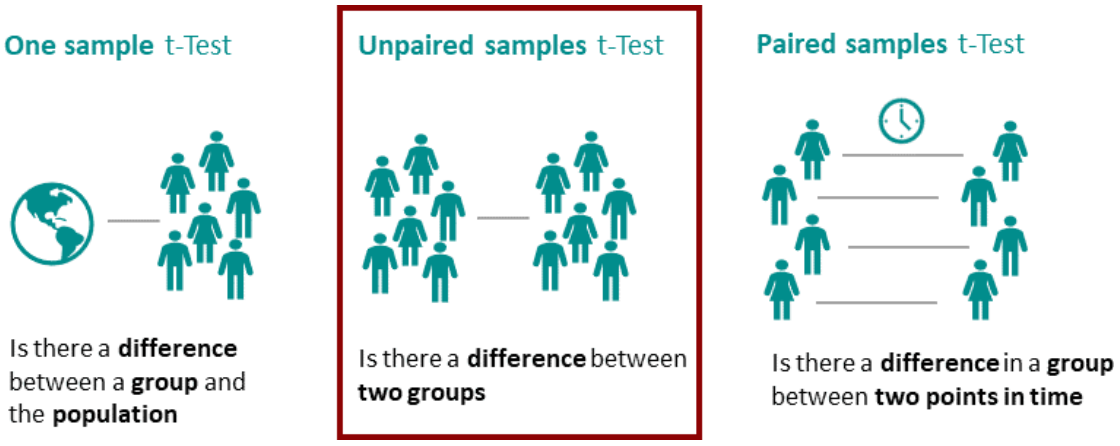

One sample t-Test
Is there a difference between a group and the population
Unpaired samples t-Test
Is there a difference between two groups
Paired samples t-Test
Is there a difference in a group between two points in time

Figure 5.2.22 Different kinds of t-test (DATAtab Team, 2022)

From the figure above it can be seen that an unpaired samples t-test would be the t-test that would be most appropriate when looking at the difference between two groups. We are eager to see the difference between the real values and the values from the model to determine if the model is sufficiently similar.

Table 5.2-19 Comparison between real and predicted values when the neural network is applied to the original dataset.

| | *Compressive Strength (Source)* | *Compressive Strength (Predicted)* |
|---|---|---|
| Mean | 29.41937114 | 29.24153998 |
| Variance | 138.6808975 | 131.5377093 |
| Observations | 270 | 270 |
| Hypothesized Mean Difference | 0 | |
| df | 538 | |
| t Stat | 0.177759205 | |
| P(T<=t) one-tail | 0.429489497 | |
| t Critical one-tail | 1.647690825 | |
| P(T<=t) two-tail | 0.858978995 | |
| t Critical two-tail | 1.964383179 | |

From the table above, the P(T<=t) is greater than 0.05 for both one-tail and two-tail. This would indicate that the predictions are sufficiently similar with the real values. The predictions, however, are only sufficiently accurate for the 10-60 MPa range. This could be seen as the values above 60 MPa are scarce.

#### V.2.5.2 Tweaked neural network constants

The original functionality of the code that was derived would be attained by replacing the neural network constants written in section III.1.3.1 with the neural network constants

below. This is possible since the neural network constants are the only thing that changed between different models and iterations.

```
%
% Auto-generated by MATLAB, 11-Jul-2022 21:08:33.
%
% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.keep = [1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 18 19 20 21];
x1_step2.xoffset =
[0;0;0;0;0;35;0.1;1285.5;0;0;0;0;0;0;0;0;14;2.93890080756283;7];
x1_step2.gain =
[0.00389105058365759;0.00155038759689922;0.00173897921919
833;0.00306748466257669;0.002439024390243902;0.008264462809
91736;2.89855072463768;0.00177856825255669;0.006071645415
90771;0.004;0.0097799511002445;0.248138957816377;0.0192492
781520693;0.00579206487112656;0.004;0.571428571428571;0.05
26868947757209;0.869905920796697;0.0240963855421687];
x1_step2.ymin = -1;

% Layer 1
b1 = [-2.9114928109822271196;1.06050295051008380830;-
0.79305235122293715744;-
1.68493690351471858690;2.54970054794793687950];
IW1_1 = [-0.36521660578107323358 -1.7908717578888597721 -
1.69762131807384708540 -1.13147836278172952970 -
1.12850592164735852310 0.10736070196759561757 -
0.32809957575717074718 1.16953002911370429470 -
0.63744051638111887126 -0.50168888359831331769 -
0.37572352355358273890 0.17891227807019860485 -
0.00512699207989560090670 0.15712226737440698754 -
0.50071083909786329169 0.97795892887253388359
0.60040494135135169529 0.79017646355612081166
0.07141118828054736356;-0.94962302152461519622 -
1.85136560409668549100 -0.20865229728945552945 -
0.12259441027631814980 -2.20808335075653605630
0.27863626072012587231 0.45636873011938600131 -
0.52954400956060931893 -0.99263653077281888137 -
1.19026719523492530150 -1.60024417073996638730 -
1.63668366245124130560 -0.59521006730462300283
```

1.8655631310795446343 -0.65296021590202413254
1.0975522786962528254 2.1035758386240241968
4.0396743979728917395 -
4.723542786624203238;2.3448092612006949942
2.2588418090303652441 0.08282311042190994288
0.068734407347494391738 2.385176983974686582 -
1.6887467159487292712 -0.607629039341412657 83 -
4.563366184729527042 -3.0248955399863204363
1.860677104937902282 -5.2685481755096299494 -
1.3792012865618619166 0.39083660531367048208
1.8546075819441658616 0.67266144924099569025
0.72885222224803780655 -0.081444732517545304074 -
0.74950391707580532596
0.029419666739508562592;1.0649803353098585834
1.7878886806841527424 0.58790732723916927505
1.1091732545856720638 -1.1884384534897167729
1.1996895463271515236 2.0386218958500452736
0.18327487829565505817 0.840104584634057238 72 -
2.1656836891612170071 1.00407520679825035 26 -
1.8292818394949448 28 0.690673736558576223 39 -
0.614563116383051388 78 -1.608721992302377668 -
0.004621251441123994802 0.23383216587691454946 -
1.9443343435189333057 -
1.8433976026778366997;3.5747660475842213401 -
1.4819499879069830683 -0.049343257631359556392 -
1.1824196720745629996 -1.0957426845924105319 -
0.308589578966610322 83 0.724626572568907278 97
0.504461712787212412 93 2.0809048590192631423 -
4.008164620152664170 4 3.0992288402615422171
2.9178292341778053753 -5.3232970785532023328
1.1027488226276622729 0.856937856834886546 59
2.7504348234559667929 -1.2835063437620817 25
0.516283811803052272 72 -0.0469365117151949451 38];

% Layer 2
b2 = -0.0843949077776176420 64;
LW2_1 = [0.6181775410912169199 7 -0.0730032253662601937 63 -
0.1673708768506759758 7 0.152395696312265072 07 -
0.2502349381071734546 5];

% Output 1
y1_step1.ymin = -1;
y1_step1.gain = 0.0286728785406686;
y1_step1.xoffset = 11.117673;

## V.3 Destructive Factors

### *V.3.1 Linear Regression*

Linear regression is used here since it is the most intuitive method by which a data analysis could be understood. Linear regression is of form $y=\beta_0+\sum_{i=1}^{n}\beta_i x_i$, which makes it very intuitive to understand and use.

Table 5.3-20 Result using linear regression. The values in yellow are the ones that are deemed not significant.

| | Estimate | SE | tStat | pValue |
|---|---|---|---|---|
| (Intercept) | -5.949 | 51.492 | -0.1155 | 0.90816 |
| Cementkgm3 | -0.0071836 | 0.1829 | -0.0393 | 0.96871 |
| CoarseAggregateskgm3 | -0.29254 | 0.0468 | -6.2509 | 3.28E-09 |
| FineAggregateskgm3 | -0.19881 | 0.0545 | -3.6493 | 0.00035 |
| CoarseRCAkgm3 | -0.29672 | 0.0468 | -6.3449 | 2.01E-09 |
| FineRCAkgm3 | 0 | 0 | NaN | NaN |
| WaterContentkgm3 | -0.39942 | 0.3878 | -1.0299 | 0.30455 |
| WaterToBinderRatio | 193.11 | 87.688 | 2.2023 | 0.02902 |
| TotalUnitWeightkgm3 | 0.18636 | 0.0437 | 4.2684 | 3.29E-05 |
| GraniteFineskgm3 | 0 | 0 | NaN | NaN |
| FlyAshContentkgm3 | -0.17033 | 0.204 | -0.8327 | 0.4062 |

| | | | | |
|---|---|---|---|---|
| | | 6 | | |
| GroundGranulatedBlastFurnaceSlagGGBSkgm3 | 0 | 0 | NaN | NaN |
| NanoSilicakgm3 | -0.55449 | 0.2121 | -2.6138 | 0.00977 |
| Fillerkgm3 | 0.52875 | 0.3317 | 1.5941 | 0.1128 |
| CrumbRubberkgm3 | -0.15206 | 0.0383 | -3.9741 | 0.0001 |
| MetakaoliniteContentkgm3 | 0 | 0 | NaN | NaN |
| polypropyleneFibreByVolume | 15.333 | 10.357 | 1.4803 | 0.14067 |
| dryCuring | -2.5802 | 0.8802 | -2.9313 | 0.00385 |
| Superplasticizer | 26 | 23.311 | 1.1153 | 0.26632 |
| SchmidtReboundNumber | 0 | 0 | NaN | NaN |
| UPVkms | 0 | 0 | NaN | NaN |
| AgeOfConcretedays | 0.33389 | 0.0206 | 16.235 | 3.53E-36 |

The estimate shows what the coefficient that would be attached to the factor would be. The standard error shows the variability of a coefficient. In order words, it shows how far apart the value that would have been predicted by regression from the other values. tStat is the estimate over the standard error. The pValue is the probability of the coefficient being insignificant, with 0.05 being the p value that is the threshold whether the value would be removed. The result from the linear regression shows the importance of each of the variables and coefficient that they would add to the model. The NaN would indicate factors that do not exist within the

dataset.

Table 5.3-21 Model training results

| | |
|---|---|
| RMSE (Validation) | 4.5673 |
| R-Squared (Validation) | 0.83 |
| MSE (Validation) | 20.86 |
| MAE (Validation) | 3.3412 |
| Prediction speed | ~2200 obs/sec |
| Training time | 11.338 sec |

Table 5.3-22 Model parameters

| | |
|---|---|
| Model Type | |
| Preset | Linear |
| Terms | Linear |
| Robust option | Off |

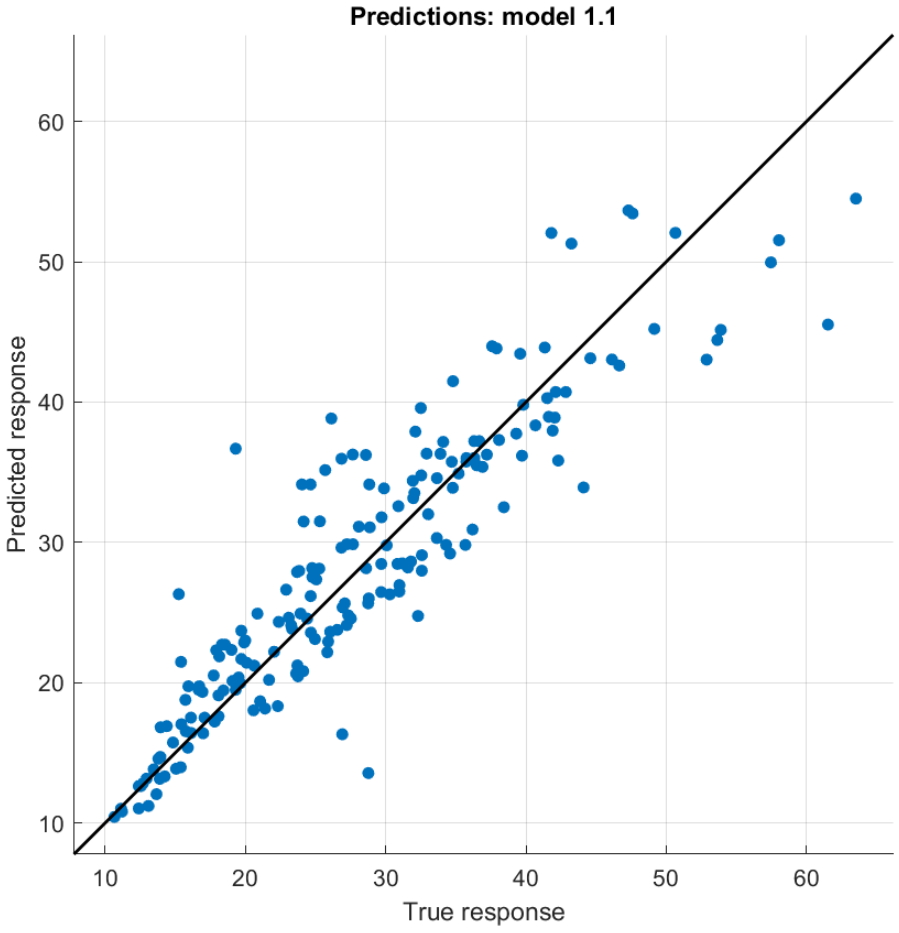



Figure 5.3.23 True vs Predicted for Linear Regression

The true vs predicted response graph shows the how much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also shows that there are outliers and that most of the reliable data is between 10 to 45 MPa compressive strength.

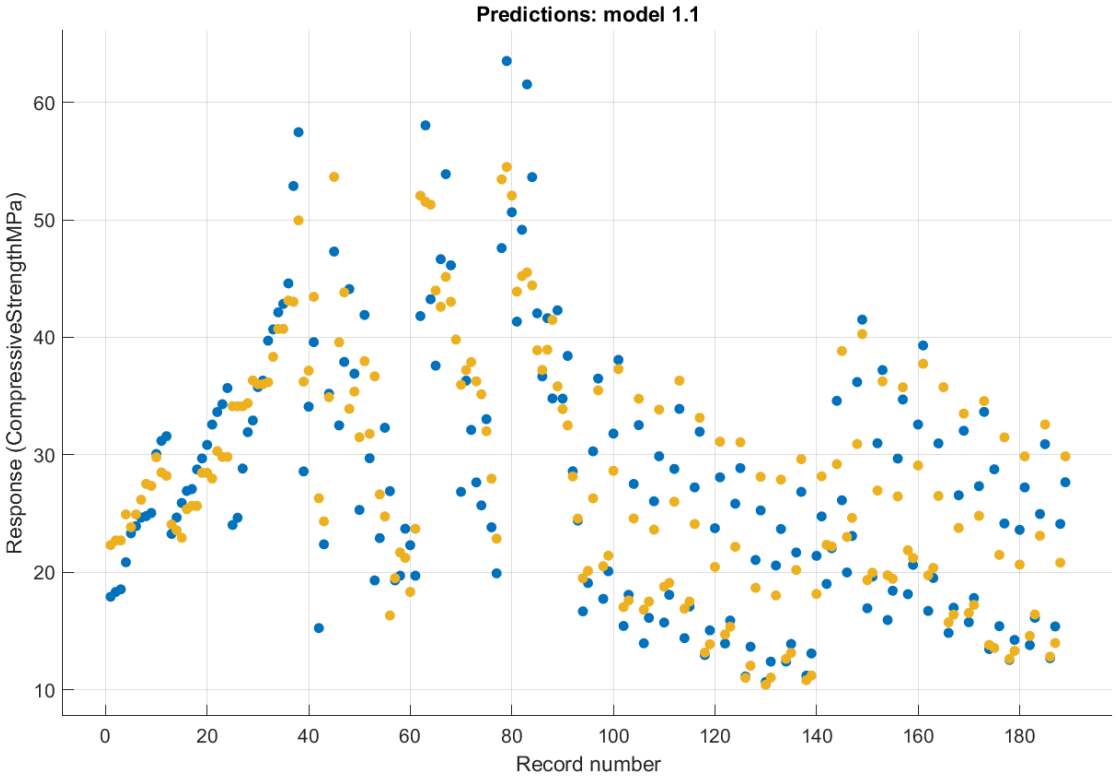



Figure 5.3.24 Response Plot for Linear Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

### *V.3.2 Rational Quadratic Gaussian Process Regression*

This part has been added to give another method by which the neural network method should be able to beat.

Table 5.3-23 Model training results

| | |
|---|---|
| RMSE (Validation) | 4.5673 |

| | |
|---|---|
| RMSE (Validation) | 3.6875 |
| R-Squared (Validation) | 0.89 |
| MSE (Validation) | 13.598 |
| MAE (Validation) | 2.3009 |
| Prediction speed | ~5800 obs/sec |

Table 5.3-24 Model parameters

| Model Type | |
|---|---|
| Preset | Rational Quadratic GPR |
| Basis function | Constant |
| Kernel function | Rational Quadratic |
| Use isotropic kernel | true |
| Kernel scale | Automatic |
| Signal standard deviation | Automatic |
| Sigma | Automatic |
| Standardize | true |
| Optimize numeric parameters | true |

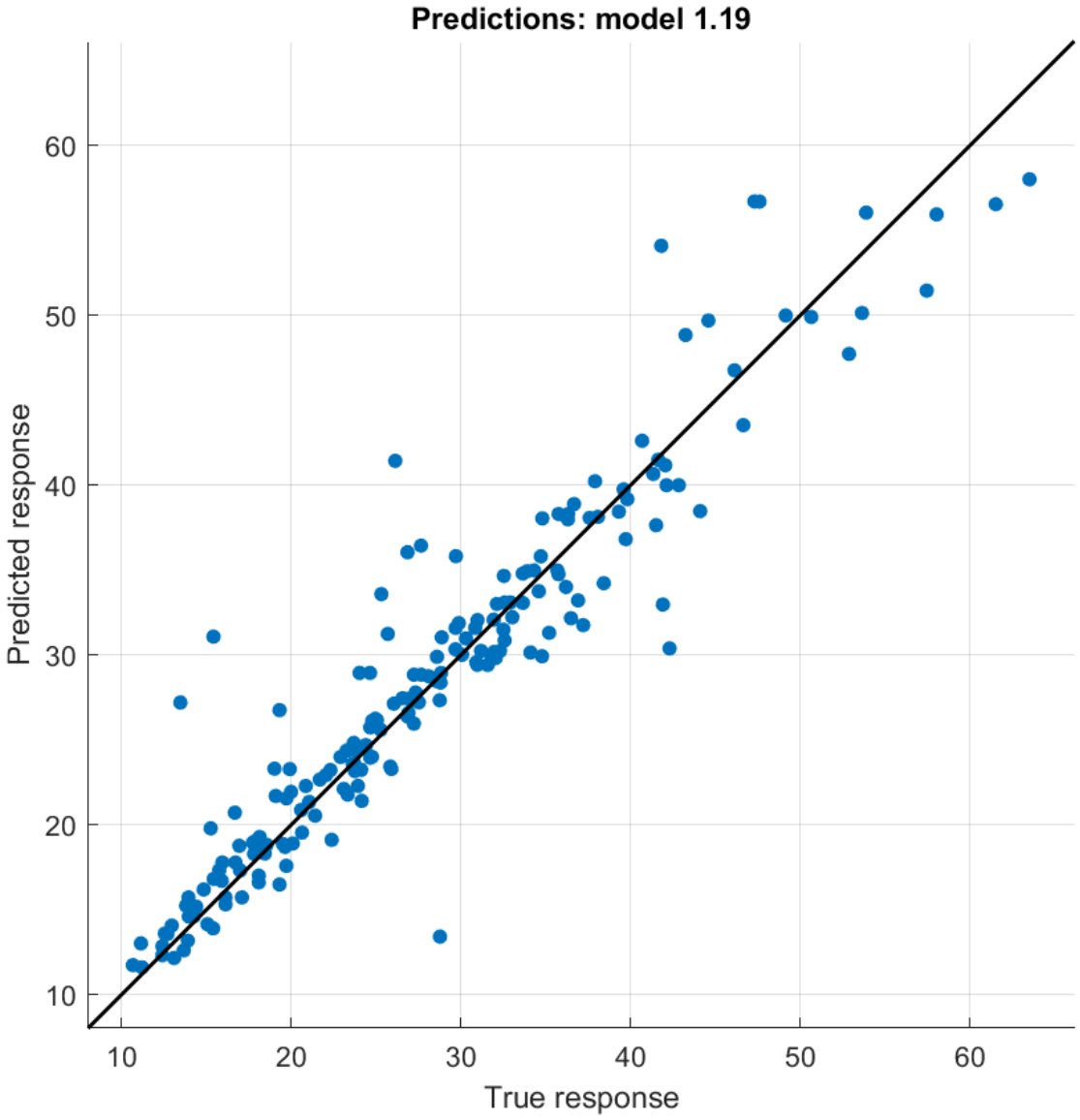



Figure 5.3.25 Predicted vs Actual for Rational Quadratic Gaussian Process Regression

The true vs predicted response graph shows the how much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also

shows that there are outliers and that most of the reliable data is between 10 to 45 MPa compressive strength.

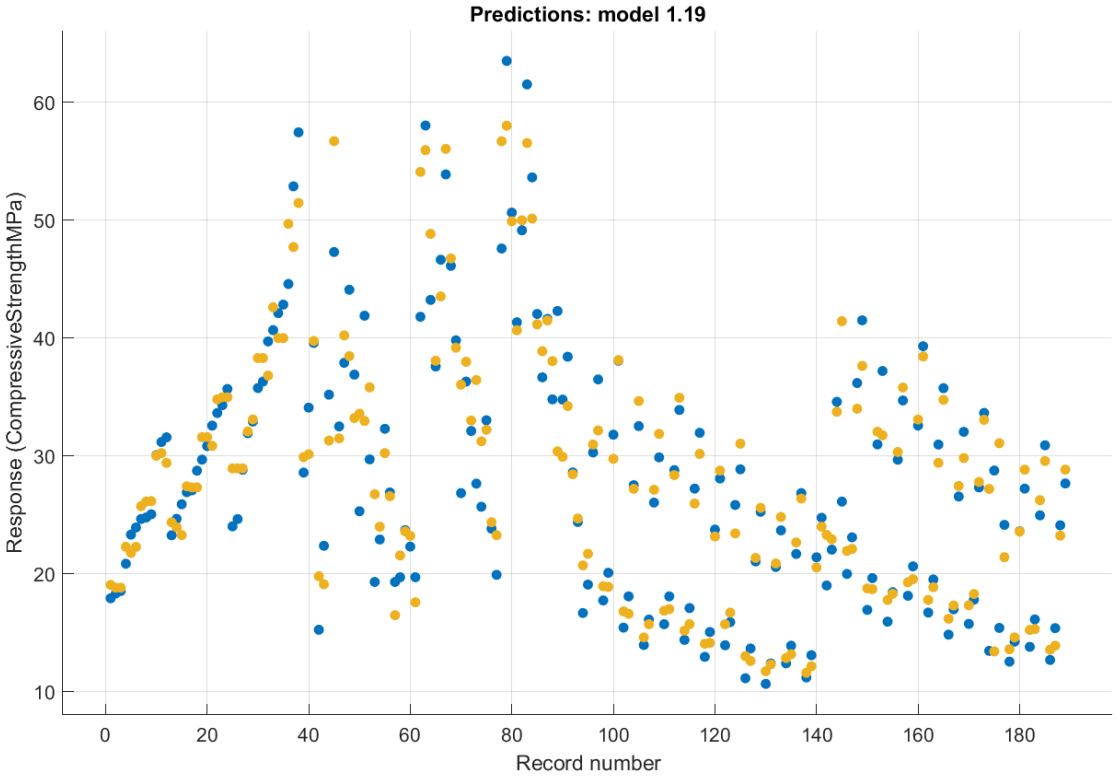



Figure 5.3.26 Response Plot for Rational Quadratic Gaussian Process Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

### *V.3.3 Tweaked neural network for destructive testing factors only*

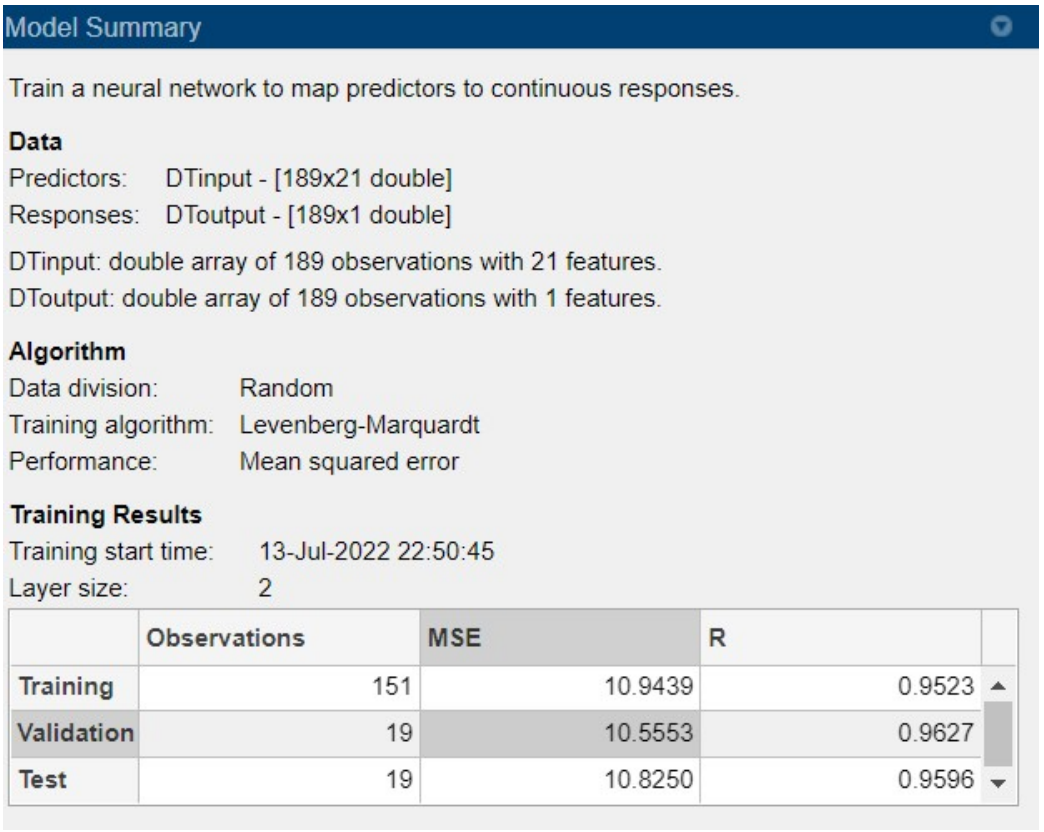

Model Summary
Train a neural network to map predictors to continuous responses.
Data
Predictors: DTinput - [189x21 double]
Responses: DToutput - [189x1 double]
DTinput: double array of 189 observations with 21 features.
DToutput: double array of 189 observations with 1 features.
Algorithm
Data division: Random
Training algorithm: Levenberg-Marquardt
Performance: Mean squared error
Training Results
Training start time: 13-Jul-2022 22:50:45
Layer size: 2
Observations MSE R
Training 151 10.9439 0.9523
Validation 19 10.5553 0.9627
Test 19 10.8250 0.9596

Figure 5.3.27 Model Summary.

The Figure above shows the summary of the model. The R value shown indicates that the model created is a good match to the data given. Moreover, the closeness of the mean square error between training, validation and test means that no overfitting has occurred. The test-train ratio of 80:20 is also implemented. This result is chosen since the mean squared error is lower than the value obtained using other methods, such as stepwise regression.

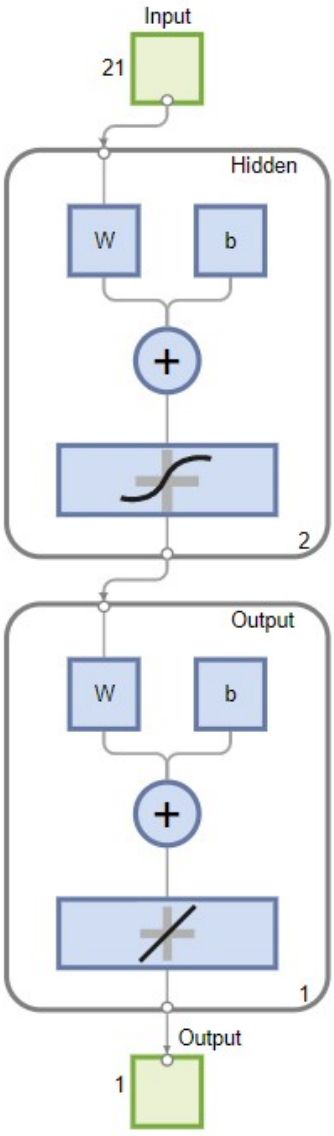



Figure 5.3.28 Diagram of the neural network.

The Figure above shows that a sigmoid activation is used. It also shows that there are twenty-one features as input and one as output. It also shows that the hidden layer has a size of two.

**Training Results**

Training finished: Met validation criterion

**Training Progress**

| Unit | Initial Value | Stopped Value | Target Value |
|---|---|---|---|
| Epoch | 0 | 24 | 1000 |
| Elapsed Time | - | 00:00:00 | - |
| Performance | 116 | 10.8 | 0 |
| Gradient | 436 | 3.55 | 1e-07 |
| Mu | 0.001 | 0.01 | 1e+10 |
| Validation Checks | 0 | 6 | 6 |

Figure 5.3.29 Training progress with elapsed time and different stopping criteria

The Figure above shows that the machine learning run is successful. Namely, the mean squared error has decreased. This is shown under performance. The training was finished by meeting the validation criteria, which is that for six consecutive iterations, the validation error increases.

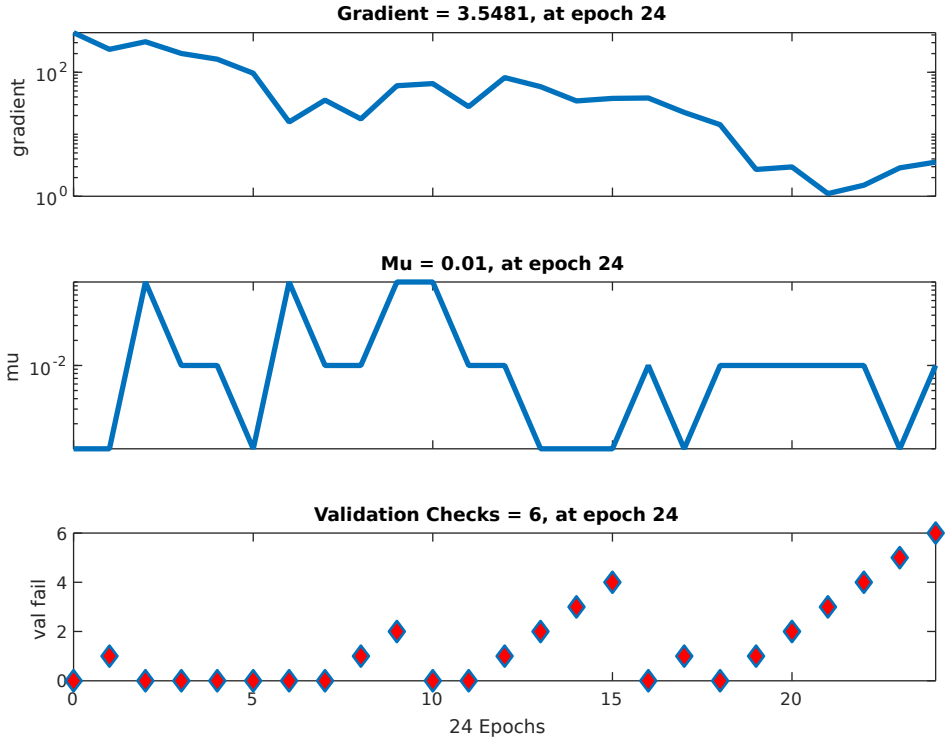



Figure 5.3.30 Different charts showing the various training parameters.

The gradient chart shows that the steps needed to reach the goal gets smaller, which is the expected outcome.

The mu chart measures how near to the newton's method the analysis would be. A high mu would create the algorithm be equivalent to gradient descent with little steps, whereas a small mu would create the algorithm be nearer to newton's method. it is useful to induce to Newton's method as quickly as attainable since it is quicker and is more accurate

close to an error minimum. Thus, mu is shrunken after every successful step (reduction in performance function) and is augmented only if a tentative step would increase the performance function. in this approach, the performance function is always reduced at every iteration of the algorithm.

The validation checks show the accumulated amount of validation checks failed in a row. The chart looks as expected since the six failures of each epoch to increase the performance on the validation test caused the test to be finished.

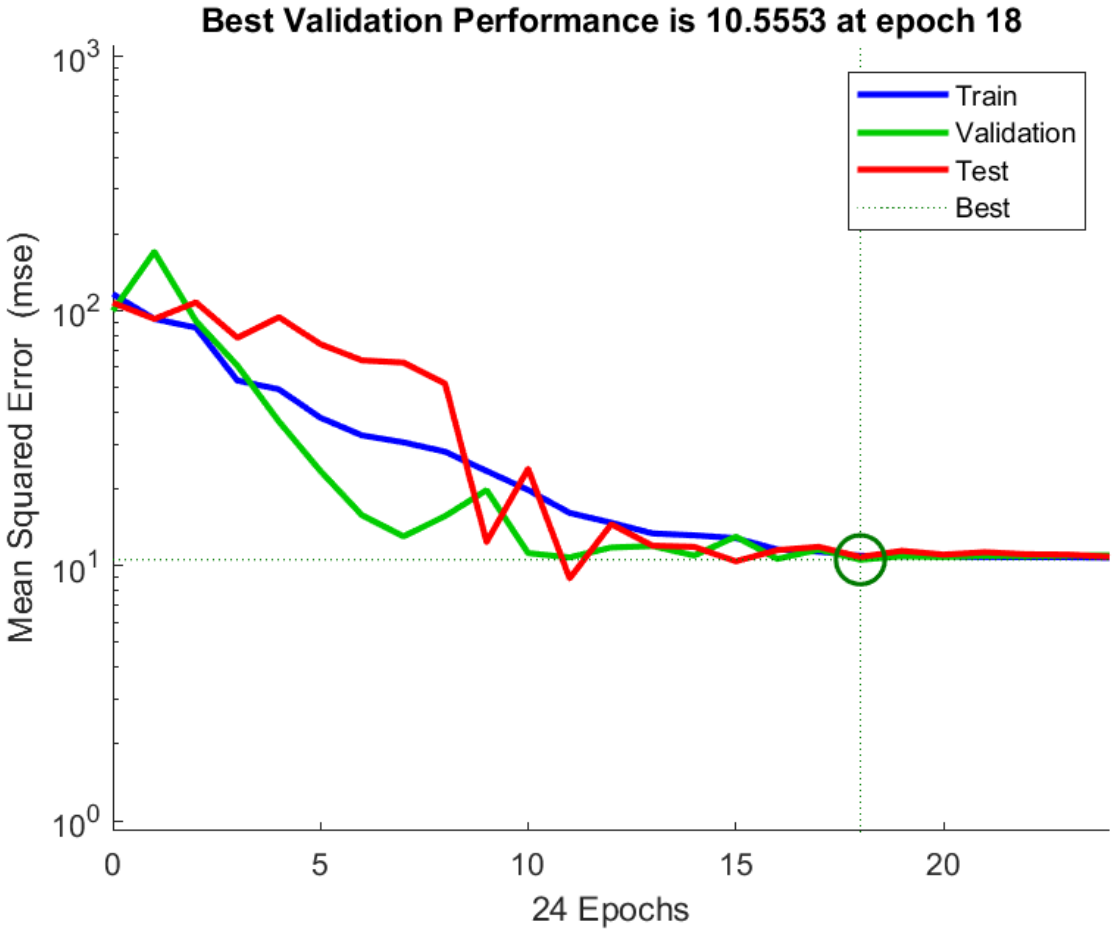



Figure 5.3.31 Performance (Mean squared error) for each of the epochs or train, validation, and test.

The Figure above shows that the neural network is improving. I also show that the best version of the neural network was found on epoch eighteen.

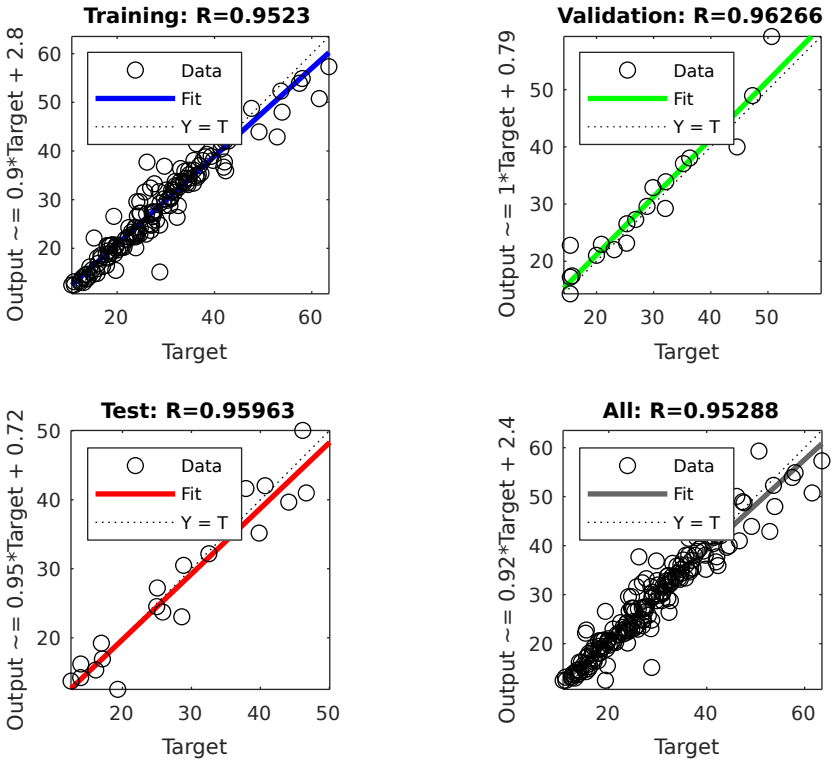



Figure 5.3.32 Charts showing the correlation between the target and the output.

The Figure above shows that the neural network is predicting well. Moreover, it demonstrates that there is much alignment between the output of the neural network and the target value.

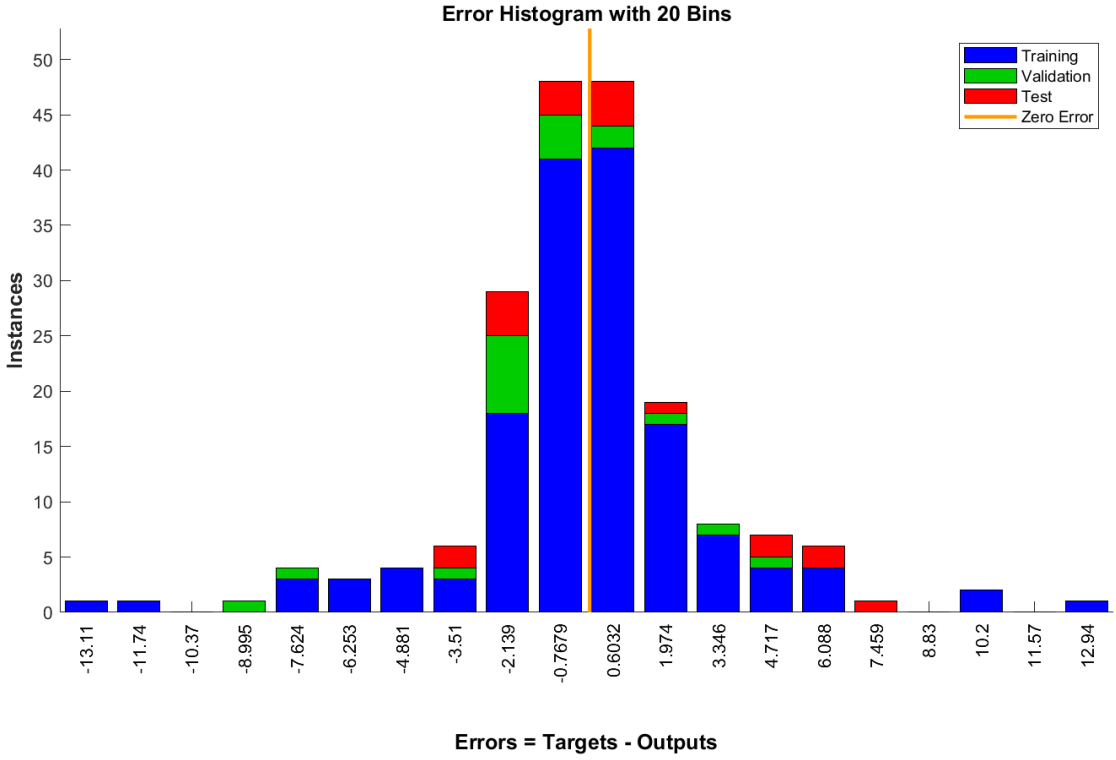



Figure 5.3.33 Error histogram of the neural network.

The error histogram mostly follows the curve expected from the neural network, namely that except for outliers, the errors follow the normal distribution. Nevertheless, the outliers show the blind spots of the model.

### V.3.3.1 Comparison between predicted values vs real values

The comparison of predicted values vs real values is used to see to what extent the predictions will align with the real data. The comparison is as follows:

Table 5.3-25 Comparison between real and predicted values when the neural network is applied to the original dataset.

| Compressive Strength (Source) | Compressive Strength (Predicted) |
|---:|---:|
| 17.92155855 | 20.57 |
| 18.3254812 | 20.57 |
| 18.54422754 | 20.57 |
| 20.8558458 | 22.96 |
| 23.32262387 | 22.96 |
| 23.9292315 | 22.96 |
| 24.65347537 | 27.22 |
| 24.77819508 | 27.22 |
| 25.05006746 | 27.22 |
| 30.07010786 | 31.98 |
| 31.18801294 | 31.98 |
| 31.5817028 | 31.98 |
| 23.26824437 | 22.93 |
| 24.66417555 | 22.93 |
| 25.89965488 | 22.93 |
| 26.92654678 | 24.79 |
| 27.0824143 | 24.79 |
| 28.75111365 | 24.79 |
| 29.68631878 | 28.77 |
| 30.84157217 | 28.77 |
| 32.57445226 | 28.77 |
| 33.64413133 | 33.38 |
| 34.30733235 | 33.38 |
| 35.68263401 | 33.38 |
| 24.02605286 | 29.58 |
| 24.64292245 | 29.58 |
| 28.82976209 | 29.58 |
| 31.93005181 | 33.73 |
| 32.91842391 | 33.73 |
| 35.76234635 | 38.06 |
| 36.31706604 | 38.06 |
| 39.7150431 | 38.06 |
| 40.67657424 | 42.04 |
| 42.12350638 | 42.04 |

| | |
|---|---|
| 42.8434002 | 42.04 |
| 44.59 | 39.99 |
| 52.88 | 42.89 |
| 57.46 | 53.91 |
| 28.59 | 31.64 |
| 34.1 | 34.39 |
| 39.59 | 47.16 |
| 15.25 | 22.12 |
| 22.38 | 24.26 |
| 35.2 | 37.07 |
| 47.3033537 | 48.96 |
| 32.50580381 | 32.83 |
| 37.90490985 | 41.62 |
| 44.10388345 | 39.66 |
| 36.9050754 | 36.99 |
| 25.30699576 | 26.54 |
| 41.90424766 | 36.68 |
| 29.70626735 | 36.87 |
| 19.30798905 | 26.58 |
| 22.90739308 | 23.33 |
| 32.30583692 | 26.37 |
| 26.90673088 | 23.69 |
| 19.30798905 | 12.53 |
| 19.70792283 | 20.46 |
| 23.70726064 | 24.31 |
| 22.30749241 | 22.34 |
| 19.70792283 | 15.48 |
| 41.81 | 45.90 |
| 58.04 | 54.89 |
| 43.24 | 57.03 |
| 37.59 | 38.04 |
| 46.65 | 40.98 |
| 53.89 | 47.97 |
| 46.13 | 50.05 |
| 39.81 | 35.18 |
| 26.85 | 32.41 |
| 36.31 | 41.50 |
| 32.12 | 33.90 |
| 27.65 | 33.27 |

| | |
|---:|---:|
| 25.69 | 31.59 |
| 33.03 | 36.39 |
| 23.83 | 20.12 |
| 19.91 | 20.68 |
| 47.6 | 48.75 |
| 63.52 | 57.31 |
| 50.65 | 59.30 |
| 41.34 | 40.41 |
| 49.15 | 43.92 |
| 61.53 | 50.76 |
| 53.64 | 52.31 |
| 42.05 | 37.73 |
| 36.67 | 35.21 |
| 41.63 | 44.43 |
| 34.8 | 35.16 |
| 42.3 | 35.92 |
| 34.78 | 34.36 |
| 38.42 | 39.30 |
| 28.6 | 23.04 |
| 24.4 | 23.62 |
| 16.67408745 | 18.56 |
| 19.08407654 | 19.42 |
| 30.29733684 | 29.87 |
| 36.48917792 | 34.61 |
| 17.73729623 | 18.80 |
| 20.08714893 | 19.69 |
| 31.80401899 | 31.53 |
| 38.08091366 | 38.81 |
| 15.42997543 | 17.21 |
| 18.08353808 | 17.99 |
| 27.51842752 | 27.35 |
| 32.53071253 | 32.17 |
| 13.95577396 | 16.20 |
| 16.11793612 | 16.93 |
| 26.04422604 | 27.10 |
| 29.87714988 | 32.87 |
| 15.72481572 | 17.44 |
| 18.08353808 | 18.25 |
| 28.7960688 | 29.27 |

| | |
|---:|---:|
| 33.90663391 | 35.84 |
| 14.39465479 | 16.20 |
| 17.08939061 | 16.93 |
| 27.22693625 | 27.10 |
| 31.96262869 | 32.87 |
| 12.95510303 | 14.07 |
| 15.06037891 | 14.66 |
| 23.74888792 | 22.34 |
| 28.08480194 | 25.77 |
| 13.93592784 | 14.24 |
| 15.89423096 | 14.85 |
| 25.83911346 | 23.73 |
| 28.86736346 | 30.50 |
| 11.13628718 | 13.15 |
| 13.66187707 | 13.68 |
| 21.05146811 | 20.30 |
| 25.26478927 | 23.15 |
| 10.66221347 | 12.48 |
| 12.39728002 | 12.97 |
| 20.57691384 | 20.22 |
| 23.68422317 | 24.17 |
| 12.40136479 | 13.31 |
| 13.89927435 | 13.86 |
| 21.68388678 | 21.92 |
| 26.84607622 | 27.29 |
| 11.20086269 | 12.48 |
| 13.09100365 | 12.97 |
| 21.40176799 | 20.22 |
| 24.75357757 | 24.17 |
| 19.00752454 | 20.74 |
| 22.04656081 | 21.72 |
| 34.59229666 | 33.11 |
| 26.12922092 | 37.71 |
| 19.98563305 | 21.02 |
| 23.09298341 | 22.02 |
| 36.19115808 | 34.87 |
| 41.50767557 | 41.70 |
| 16.9375 | 19.21 |
| 19.63282967 | 20.11 |

| | |
|---|---|
| 30.98008242 | 30.45 |
| 37.2103022 | 35.42 |
| 15.9375 | 18.05 |
| 18.43282967 | 18.89 |
| 29.68035714 | 30.18 |
| 34.71057692 | 36.06 |
| 18.1375 | 19.47 |
| 20.63255495 | 20.39 |
| 32.58008242 | 32.49 |
| 39.31057692 | 38.89 |
| 16.70655199 | 18.05 |
| 19.51466629 | 18.89 |
| 30.97222706 | 30.18 |
| 35.7525599 | 36.06 |
| 14.83978931 | 15.59 |
| 16.98687872 | 16.28 |
| 26.55697493 | 25.02 |
| 32.04692985 | 29.22 |
| 15.75112086 | 15.78 |
| 17.8075247 | 16.49 |
| 27.33256875 | 26.52 |
| 33.65120781 | 33.75 |
| 13.46266875 | 14.51 |
| 28.76499645 | 15.14 |
| 15.41032044 | 22.79 |
| 24.15249252 | 26.64 |
| 12.54481036 | 13.72 |
| 14.24440116 | 14.30 |
| 23.61437592 | 22.63 |
| 27.22875185 | 27.49 |
| 13.80041575 | 14.70 |
| 16.12780923 | 15.34 |
| 24.9596674 | 24.52 |
| 30.90614337 | 30.59 |
| 12.69039095 | 13.72 |
| 15.39102456 | 14.30 |
| 24.11875839 | 22.63 |
| 27.66379635 | 27.49 |

It could be seen that there are some differences

between the real value and the predicted value.

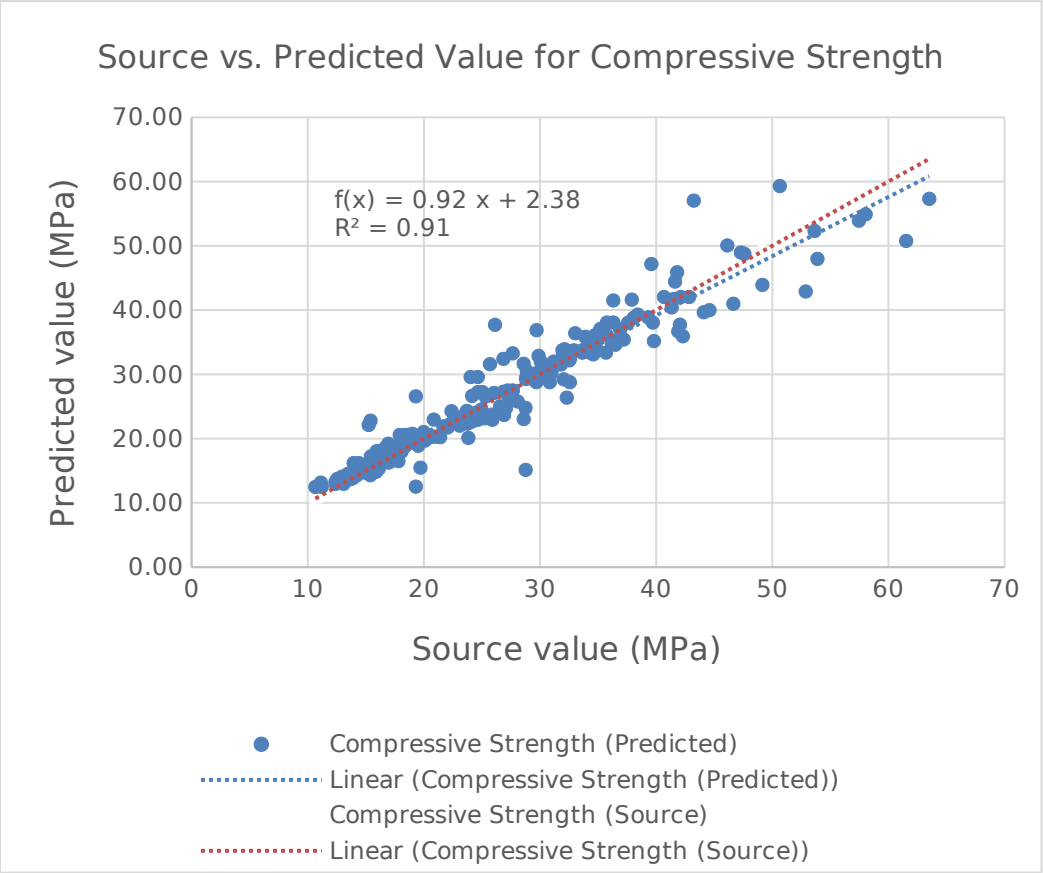



Figure 5.3.34 Source vs. Predicted Value for Compressive Strength

The chart would confirm the extent of similarity between the source value and the predicted value. The comparison between the y=x trendline also highlights the difference between the real and predicted values. The graph also shows the areas where the outliers are.

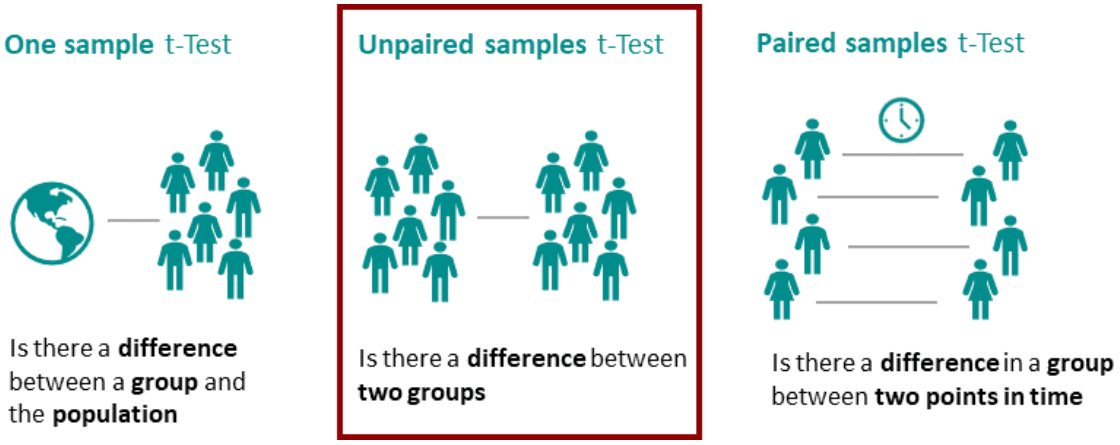

One sample t-Test
Is there a difference between a group and the population
Unpaired samples t-Test
Is there a difference between two groups
Paired samples t-Test
Is there a difference in a group between two points in time

Figure 5.3.35 Different kinds of t-test (DATAtab Team, 2022)

From the figure above it can be seen that an unpaired samples t-test would be the t-test that would be most appropriate when looking at the difference between two groups. We are eager to see the difference between the real values and the values from the model to determine if the model is sufficiently similar.

Table 5.3-26 Comparison between real and predicted values when the neural network is applied to the original dataset.

| | *Compressive Strength (Source)* | *Compressive Strength (Predicted)* |
|---|---|---|
| Mean | 28.1145082 | 28.24733733 |
| Variance | 118.609677 | 110.5988537 |
| Observations | 189 | 189 |
| Hypothesized Mean Difference | 0 | |
| df | 376 | |
| t Stat | -0.120617089 | |

| | | |
|---|---|---|
| P(T<=t) one-tail | 0.45202938 | |
| t Critical one-tail | 1.648916269 | |
| P(T<=t) two-tail | 0.904058759 | |
| t Critical two-tail | 1.966293229 | |

From the table above, the P(T<=t) is greater than 0.05 for both one-tail and two-tail. This would indicate that the predictions are sufficiently similar with the real values. The predictions, however, are only sufficiently accurate for the 10-42 MPa range. This could be seen as the values above 42 MPa are scarce.

#### V.3.3.2 Tweaked neural network constants

The original functionality of the code that was derived would be attained by replacing the neural network constants written in section III.1.3.1 with the neural network constants below. This is possible since the neural network constants are the only thing that changed between different models and iterations.

```
%
% Auto-generated by MATLAB, 13-Jul-2022 22:56:12.
%
% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.keep = [1 2 3 4 6 7 8 10 12 13 14 16 17 18 21];
x1_step2.xoffset =
[134.6;0;362.5;0;96.9;0.33;1565.35;0;0;0;0;0;0;0;3];
x1_step2.gain =
[0.00534188034188034;0.0020242914979757;0.00253936008125
```

```
952;0.00202429149797571;0.0137835975189524;9.090909090909
09;0.00240196961508437;0.0195121951219512;0.2481389578163
77;0.0192492781520693;0.00579206487112656;20;2;1.666666666
66667;0.0377358490566038];
x1_step2.ymin = -1;

% Layer 1
b1 = [2.5430977352346637588;-9.13821315437508729 93];
IW1_1 = [-0.29346197381831606865 4.7402130464559926182
2.631100712658445584 4.8094416349432238533
1.2915264196263442908 -0.72253292923563483541 -
2.4005504819454901444 0.20435252178906523901 -
0.18907576534553460768 -0.76123515660668772398
0.85255204055838507138 -0.005534632306831427719 9
0.050505046506485691549 -0.34136818316556299946 -
0.55490083327924466516;-3.7798396072313593663
2.8869943041344634516 5.4929138791179177304
2.7776691995891127362 0.47194011553239623158 -
3.565539346908419116 1.5485215482395500164
0.43480484276587494374 -14.895104410095123981
3.4220597560976471208 -1.3564644620896748606
0.49608514012807730653 0.018173699611249316543 -
3.208119310204490926 -2.5370685010539615334];

% Layer 2
b2 = -0.17127292492880508146;
LW2_1 = [-1.3291295220081387196 0.33387503439469362609];

% Output 1
y1_step1.ymin = -1;
y1_step1.gain = 0.0378373770662546;
y1_step1.xoffset = 10.6622134653275;
```

### V.4 Needed variables for NDT and DT

The needed variables could be found using both PCA and linear regression as a basis for the values.

Table 5.4-27 Different variables deemed necessary by different analysis.

| | PCA NDT | Linear Regression NDT | PCA DT | Linear Regression DT |
|---|---|---|---|---|
| Cement (kg/m^3) | 1 | 2 | 1 | |
| Coarse aggregates (kg/m^3) | 1 | 2 | 1 | 2 |
| Fine aggregates (kg/m^3) | 1 | 2 | 1 | 2 |
| Coarse RCA (kg/m^3) | 1 | 2 | 1 | 2 |
| Fine RCA (kg/m^3) | 1 | 2 | | |
| Water content (kg/m^3) | 1 | 2 | 1 | |
| Water to binder ratio | | | | 2 |
| Total Unit Weight (kg/m^3) | 1 | 2 | 1 | 2 |
| Granite Fines (kg/m^3) | | 2 | | |
| Fly ash content (kg/m^3) | | 2 | | |
| Ground Granulated Blast Furnace Slag (GGBS) (kg/m^3) | | 2 | | |
| Nano Silica (kg/m^3) | | | | 2 |
| Filler (kg/m^3) | 1 | 2 | 1 | |
| Crumb Rubber (kg/m^3) | 1 | 2 | 1 | 2 |
| Metakaolinite Content (kg/m^3) | | 2 | | |
| polypropylene fibre (% by volume) | | | | |
| dry curing | | | | 2 |

| | | | | |
|---|---|---|---|---|
| Superplasticizer (%) | | 2 | | |
| (Schmidt) Rebound number | | 2 | | |
| UPV (km/s) | | 2 | | |
| Age of concrete (days) | | | | 2 |

The rationale for creating the table is to find the most needed factors. This would allow a minimization of the required variables while keeping most of the accuracy of the model.

Table 5.4-28 Different variables deemed necessary by different analysis. The orange variables are ones that are deemed necessary only by PCA, yellow are ones that are deemed necessary only by linear regression and green is deemed necessary by both.

| | NDT | DT |
|---|---|---|
| Cement (kg/m^3) | 3 | 1 |
| Coarse aggregates (kg/m^3) | 3 | 3 |
| Fine aggregates (kg/m^3) | 3 | 3 |
| Coarse RCA (kg/m^3) | 3 | 3 |
| Fine RCA (kg/m^3) | 3 | 0 |
| Water content (kg/m^3) | 3 | 1 |
| Water to binder ratio | 0 | 2 |

| | | |
|---|---|---|
| Total Unit Weight (kg/m^3) | 3 | 3 |
| Granite Fines (kg/m^3) | 2 | 0 |
| Fly ash content (kg/m^3) | 2 | 0 |
| Ground Granulated Blast Furnace Slag (GGBS) (kg/m^3) | 2 | 0 |
| Nano Silica (kg/m^3) | 0 | 2 |
| Filler (kg/m^3) | 3 | 1 |
| Crumb Rubber (kg/m^3) | 3 | 3 |
| Metakaolinite Content (kg/m^3) | 2 | 0 |
| polypropylene fibre (% by volume) | 0 | 0 |
| dry curing | 0 | 2 |
| Superplasticizer (%) | 2 | 0 |
| (Schmidt) Rebound number | 2 | 0 |
| UPV (km/s) | 2 | 0 |
| Age of concrete (days) | 0 | 2 |

From the analysis shown, it could be seen that the important parameters for NDT are as follows: cement, fine aggregates, coarse aggregates, coarse RCA, fine RCA, water content, total unit weight, granite fines, fly ash content, ground granulated blast furnace slag, filler, crumb rubber,

metakaolinite content superplasticizer %, rebound number, and UPV.

It could also be seen that the important parameters for DT are as follows: cement, fine aggregates, coarse aggregates, coarse RCA, water content, water-to-binder ratio, total unit weight, nano silica, filler, crumb rubber, dry curing, and age of concrete in days.

Table 5.4-29 Combined table for needed variables. The combined table uses the maximum between the two columns of the previous table.

| | Combined |
|---|---|
| Cement (kg/m^3) | 3 |
| Coarse aggregates (kg/m^3) | 3 |
| Fine aggregates (kg/m^3) | 3 |
| Coarse RCA (kg/m^3) | 3 |
| Fine RCA (kg/m^3) | 3 |
| Water content (kg/m^3) | 3 |
| Water to binder ratio | 2 |
| Total Unit Weight (kg/m^3) | 3 |

| | |
|---|---|
| Granite Fines (kg/m^3) | 2 |
| Fly ash content (kg/m^3) | 2 |
| Ground Granulated Blast Furnace Slag (GGBS) (kg/m^3) | 2 |
| Nano Silica (kg/m^3) | 2 |
| Filler (kg/m^3) | 3 |
| Crumb Rubber (kg/m^3) | 3 |
| Metakaolinite Content (kg/m^3) | 2 |
| polypropylene fibre (% by volume) | 0 |
| dry curing | 2 |
| Superplasticizer (%) | 2 |
| (Schmidt) Rebound number | 2 |
| UPV (km/s) | 2 |
| Age of concrete (days) | 2 |

We can also combine the two tables. However, we would use instead the previous table. This is because using the combined table only eliminates the need for polypropylene fibers.

## V.5 Using important NDT Factors only

### *V.5.1 Linear Regression*

Linear regression is used here since it is the most intuitive method by which a data analysis could be understood. Linear regression is of form $y=\beta_0+\sum_{i=1}^{n}\beta_i x_i$, which makes it very intuitive to understand and use.

Table 5.5-30 Result using linear regression.

| | Estimate | SE | tStat | pValue |
|---|---|---|---|---|
| (Intercept) | -48.122 | 6.0766 | -7.9192 | 8.03E-14 |
| Cementkgm3 | -0.15694 | 0.0285 | -5.5004 | 9.42E-08 |
| CoarseAggregateskgm3 | -0.17751 | 0.0286 | -6.2095 | 2.22E-09 |
| FineAggregateskgm3 | -0.18159 | 0.0286 | -6.3423 | 1.06E-09 |
| CoarseRCAkgm3 | -0.17833 | 0.0286 | -6.2291 | 2.00E-09 |
| FineRCAkgm3 | -0.17957 | 0.0286 | -6.2724 | 1.57E-09 |
| WaterContentkgm3 | -0.10097 | 0.0313 | -3.2248 | 0.00143 |
| WaterToBinderRatio | 0 | 0 | NaN | NaN |
| TotalUnitWeightkgm3 | 0.18183 | 0.0286 | 6.3612 | 9.58E-10 |
| GraniteFineskgm3 | -0.18769 | 0.0293 | -6.398 | 7.79E-10 |
| FlyAshContentkgm3 | -0.1775 | 0.0301 | -5.8952 | 1.22E-08 |

| | | | | |
|---|---|---|---|---|
| | 4 | | | |
| GroundGranulatedBlastFurnaceSlagGGBSkgm3 | -0.22157 | 0.0323 | -6.8555 | 5.61E-11 |
| NanoSilicakgm3 | 0 | 0 | NaN | NaN |
| Fillerkgm3 | 0.15921 | 0.0255 | 6.2523 | 1.76E-09 |
| CrumbRubberkgm3 | -0.07011 | 0.0137 | -5.1019 | 6.69E-07 |
| MetakaoliniteContentkgm3 | -0.22202 | 0.0313 | -7.0821 | 1.46E-11 |
| polypropyleneFibreByVolume | 0 | 0 | NaN | NaN |
| dryCuring | 0 | 0 | NaN | NaN |
| Superplasticizer | 11.682 | 1.4925 | 7.8272 | 1.45E-13 |
| SchmidtReboundNumber | 0.81317 | 0.055 | 14.774 | 7.37E-36 |
| UPVkms | 6.1574 | 0.7858 | 7.8362 | 1.37E-13 |
| AgeOfConcretedays | 0 | 0 | NaN | NaN |

The estimate shows what the coefficient that would be attached to the factor would be. The standard error shows the variability of a coefficient. In order words, it shows how far apart the value that would have been predicted by regression from the other values. tStat is the estimate over the standard error. The pValue is the probability of the coefficient being insignificant, with 0.05 being the p value that is the threshold

whether the value would be removed. The result from the linear regression shows the importance of each of the variables and coefficient that they would add to the model. The NaN would indicate factors that do not exist within the dataset.

Table 5.5-31 Model training results

| | |
|---|---|
| RMSE (Validation) | 2.7464 |
| R-Squared (Validation) | 0.95 |
| MSE (Validation) | 7.5425 |
| MAE (Validation) | 2.0293 |
| Prediction speed | ~3000 obs/sec |
| Training time | 11.983 sec |

Table 5.5-32 Model parameters

| | |
|---|---|
| Model Type | |
| Preset | Linear |
| Terms | Linear |
| Robust option | Off |

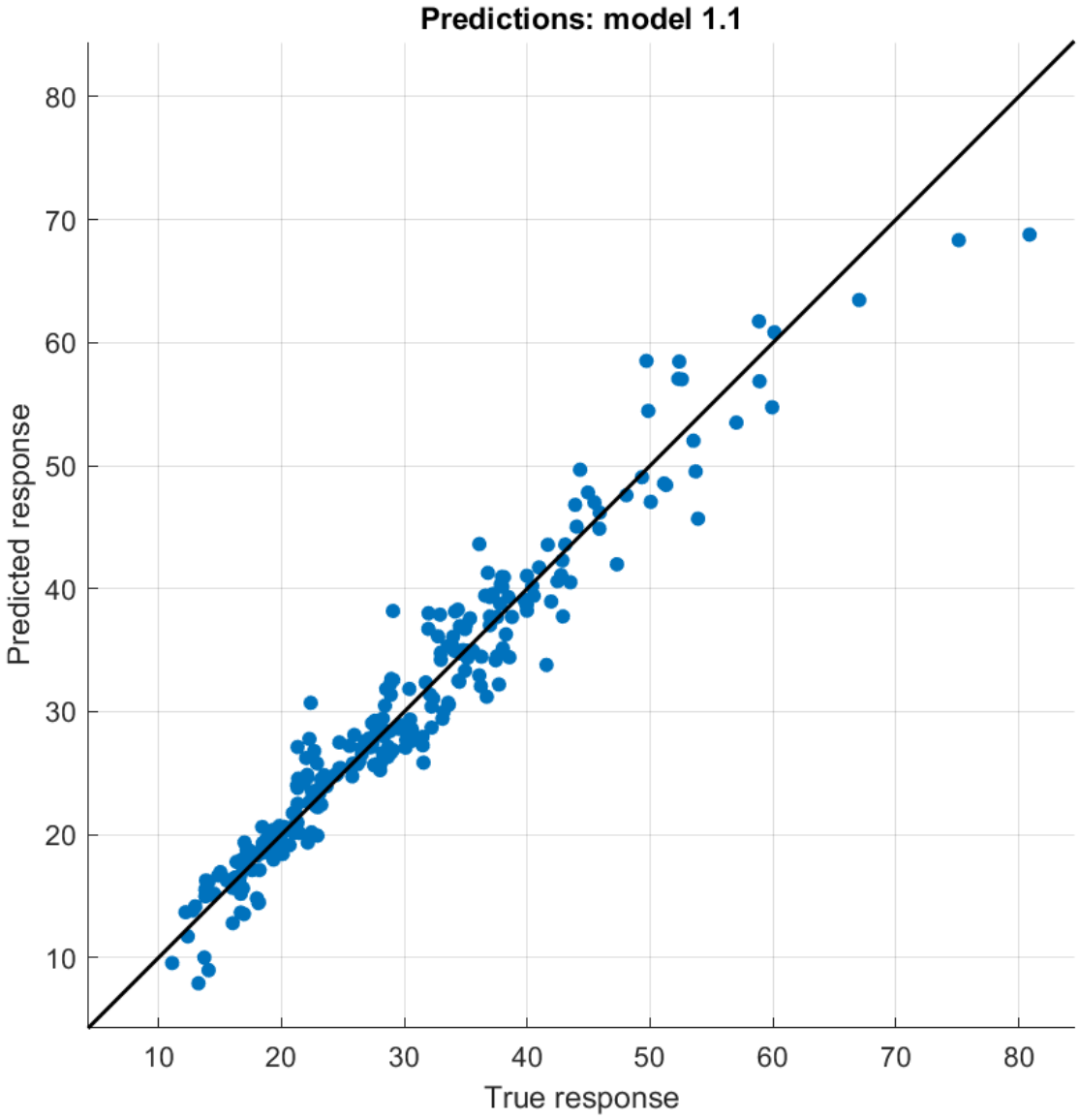



Figure 5.5.36 True vs Predicted for Linear Regression

The true vs predicted response graph shows the how much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also shows that there are outliers and that most of the reliable

data is between 10 to 45 MPa compressive strength.

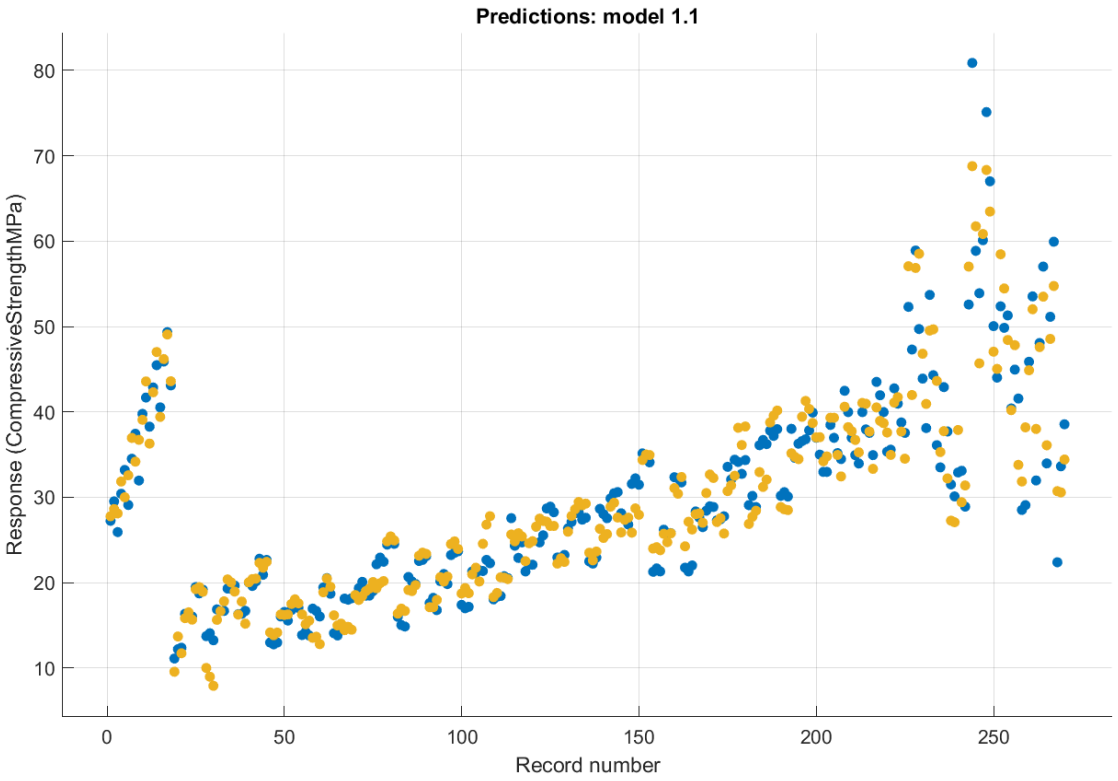



Figure 5.5.37 Response Plot for Linear Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

### *V.5.2 Stepwise Quadratic Regression with Interactions*

This part has been added to give another method by which the neural network method should be able to beat.

Table 5.5-33 Result by Stepwise Quadratic Regression with Interactions

| | Estimate | SE | tStat | pValue |
|---|---|---|---|---|
| (Intercept) | -98.848 | 8.0751 | -12.241 | 2.62E-27 |
| Cementkgm3 | -0.1286 | 0.02556 | -5.0299 | 9.38E-07 |
| CoarseAggregateskgm3 | -0.0805 | 0.02548 | -3.1608 | 0.00177 |
| FineAggregateskgm3 | -0.1638 | 0.02547 | -6.4298 | 6.44E-10 |
| CoarseRCAkgm3 | -0.1826 | 0.0259 | -7.0492 | 1.75E-11 |
| FineRCAkgm3 | -0.1664 | 0.0255 | -6.5257 | 3.74E-10 |
| WaterContentkgm3 | 0.17339 | 0.03785 | 4.5815 | 7.29E-06 |
| TotalUnitWeightkgm3 | 0.1649 | 0.02542 | 6.4883 | 4.62E-10 |
| GraniteFineskgm3 | -0.1627 | 0.02605 | -6.2456 | 1.80E-09 |
| FlyAshContentkgm3 | -0.1533 | 0.02693 | -5.6904 | 3.54E-08 |
| GroundGranulatedBlastFurnaceSlagGGBSkgm3 | -0.2113 | 0.03585 | -5.8937 | 1.22E-08 |
| Fillerkgm3 | 0.10468 | 0.01968 | 5.3198 | 2.31E-07 |
| CrumbRubberkgm3 | -0.0616 | 0.01244 | -4.9505 | 1.36E-06 |
| MetakaoliniteContentkgm3 | -0.1661 | 0.02688 | -6.1784 | 2.61E-09 |
| SchmidtReboundNumber | -0.2958 | 0.17524 | -1.688 | 0.09266 |
| UPVkms | 7.7877 | 0.75199 | 10.356 | 3.81E-21 |
| CoarseAggregateskgm3 : WaterContentkgm3 | -0.0003 | 3.25E-05 | -10.774 | 1.76E-22 |
| CoarseRCAkgm3: FineRCAkgm3 | 1.12E-05 | 4.42E-06 | 2.5469 | 0.01147 |
| GroundGranulatedBlastFurnaceSlagGGBSkgm3: SchmidtReboundNumber | 0.00125 | 0.00053 | 2.3832 | 0.01791 |
| SchmidtReboundNumber^2 | 0.0159 | 0.00262 | 6.0785 | 4.51E-09 |

The estimate shows what the coefficient that would be

attached to the factor would be. The standard error shows the variability of a coefficient. In order words, it shows how far apart the value that would have been predicted by regression from the other values. tStat is the estimate over the standard error. The pValue is the probability of the coefficient being insignificant, with 0.05 being the p value that is the threshold whether the value would be removed.

The result from the table shows the different coefficients and the result that they add to the model. A feature labeled as $A:B$ would add an interaction term $\beta_{AB}x_A x_B$ to the standard linear equation. In other

Table 5.5-34 Model training results

| | |
|---|---|
| RMSE (Validation) | 2.5959 |
| R-Squared (Validation) | 0.95 |
| MSE (Validation) | 6.7388 |
| MAE (Validation) | 1.8251 |
| Prediction speed | ~9000 obs/sec |
| Training time | 162.11 sec |

Table 5.5-35 Model parameters

| | |
|---|---|
| Model Type | |
| Preset | Stepwise Linear |
| Initial terms | Linear |
| Upper bound on terms | Quadratic |
| Maximum number of steps | 1000 |

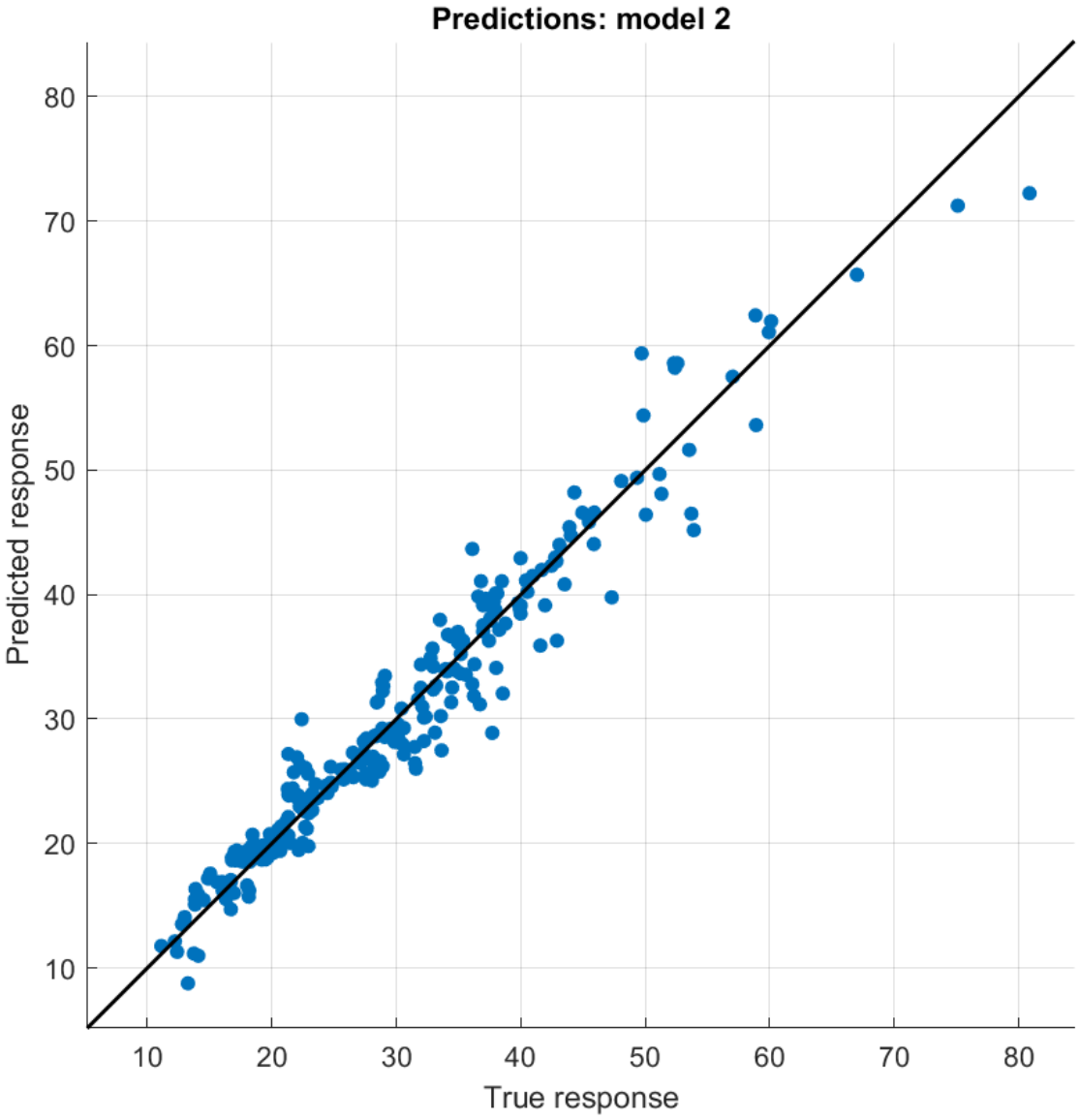


Figure 5.5.38 Predicted vs Actual for Stepwise Regression

The true vs predicted response graph shows the how much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also shows that there are outliers and that most of the reliable data is between 10 to 45 MPa compressive strength.

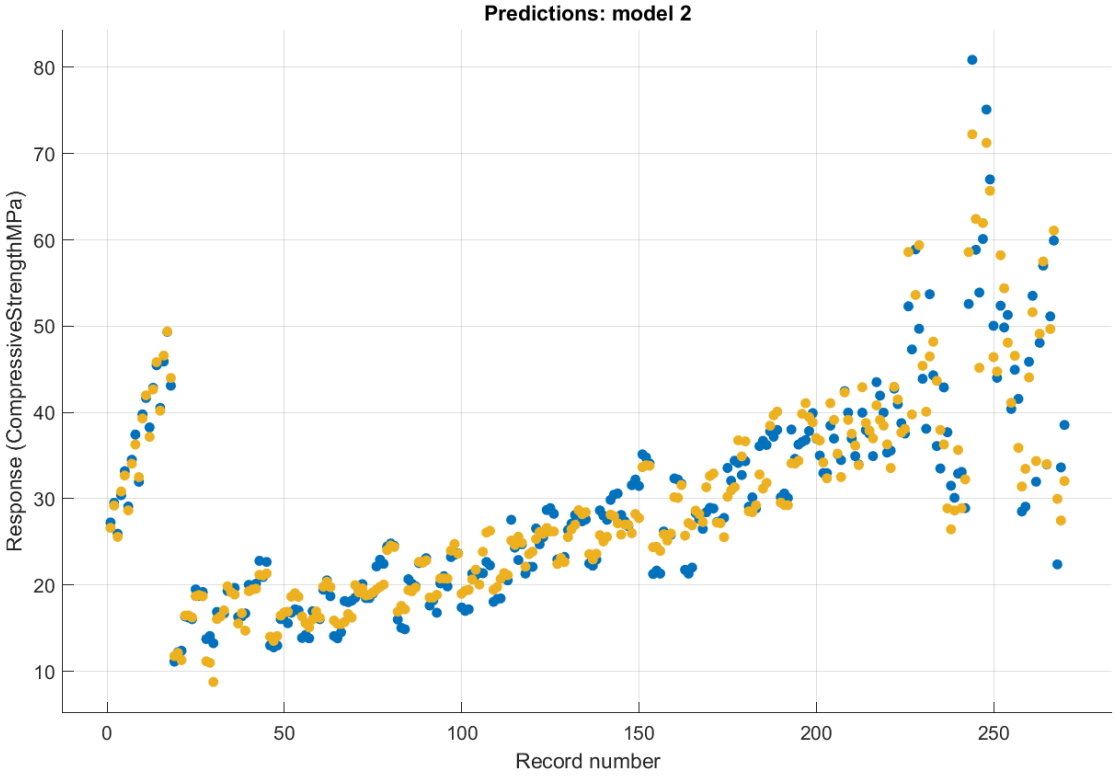



Figure 5.5.39 Response Plot for Stepwise Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed

that the results to an extent match up to the true values.

### *V.5.3Tweaked neural network for important NDT factors*

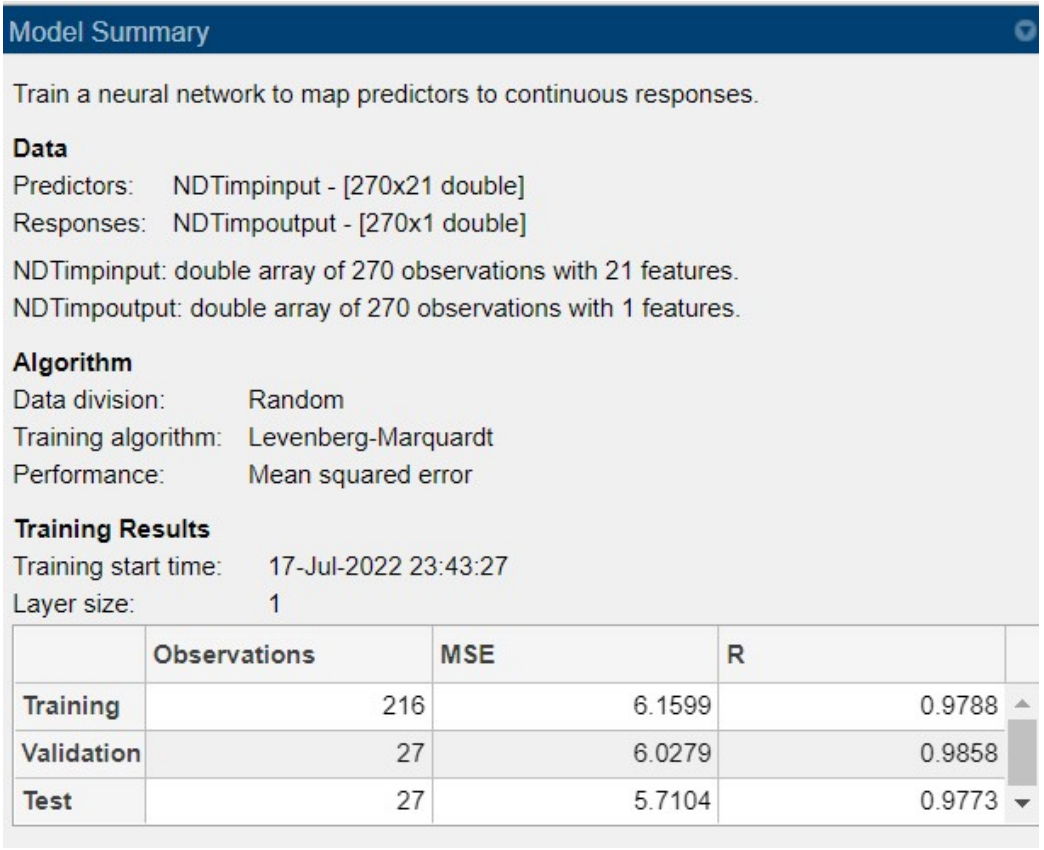

Model Summary
Train a neural network to map predictors to continuous responses.
Data
Predictors: NDTimpinput - [270x21 double]
Responses: NDTimpoutput - [270x1 double]
NDTimpinput: double array of 270 observations with 21 features.
NDTimpoutput: double array of 270 observations with 1 features.
Algorithm
Data division: Random
Training algorithm: Levenberg-Marquardt
Performance: Mean squared error
Training Results
Training start time: 17-Jul-2022 23:43:27
Layer size: 1
Observations MSE R
Training 216 6.1599 0.9788
Validation 27 6.0279 0.9858
Test 27 5.7104 0.9773

Figure 5.5.40 Model Summary.

The Figure above shows the summary of the model. The R value shown indicates that the model created is a good match to the data given. Moreover, the closeness of the mean square error between training, validation and test means that no overfitting has occurred. The test-train ratio of 80:20 is also implemented. This result is chosen since the mean squared error is lower than the value obtained using other

methods, such as stepwise regression.

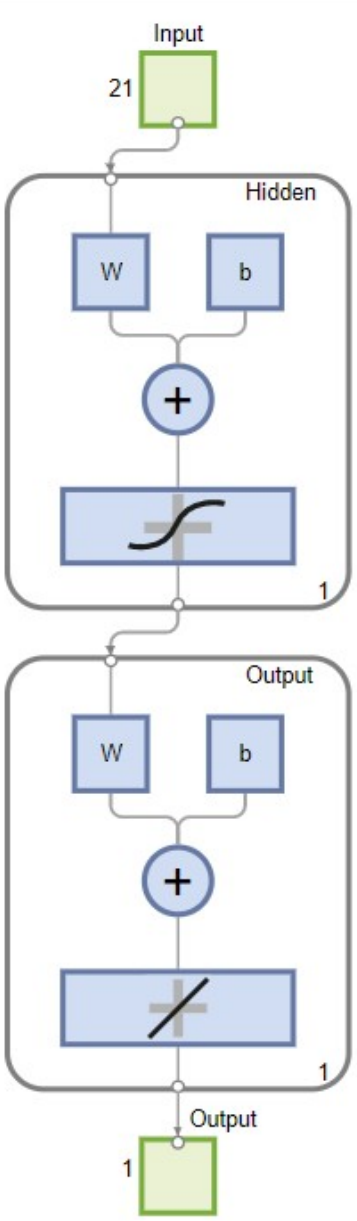
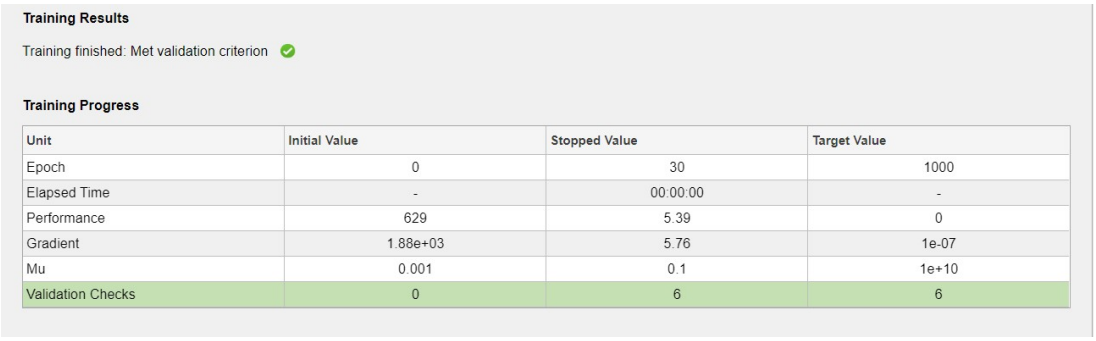



Figure 5.5.41 Diagram of the neural network.

The Figure above shows that a sigmoid activation is used. It also shows that there are twenty-one features as input and one as output. It also shows that the hidden layer

has a size of one.



**Training Results**

Training finished: Met validation criterion

**Training Progress**

| Unit | Initial Value | Stopped Value | Target Value |
|---|---|---|---|
| Epoch | 0 | 30 | 1000 |
| Elapsed Time | - | 00:00:00 | - |
| Performance | 629 | 5.39 | 0 |
| Gradient | 1.88e+03 | 5.76 | 1e-07 |
| Mu | 0.001 | 0.1 | 1e+10 |
| Validation Checks | 0 | 6 | 6 |

Figure 5.5.42 Training progress with elapsed time and different stopping criteria

The Figure above shows that the machine learning run is successful. Namely, the mean squared error has decreased. This is shown under performance. The training was finished by meeting the validation criteria, which is that for six consecutive iterations, the validation error increases.

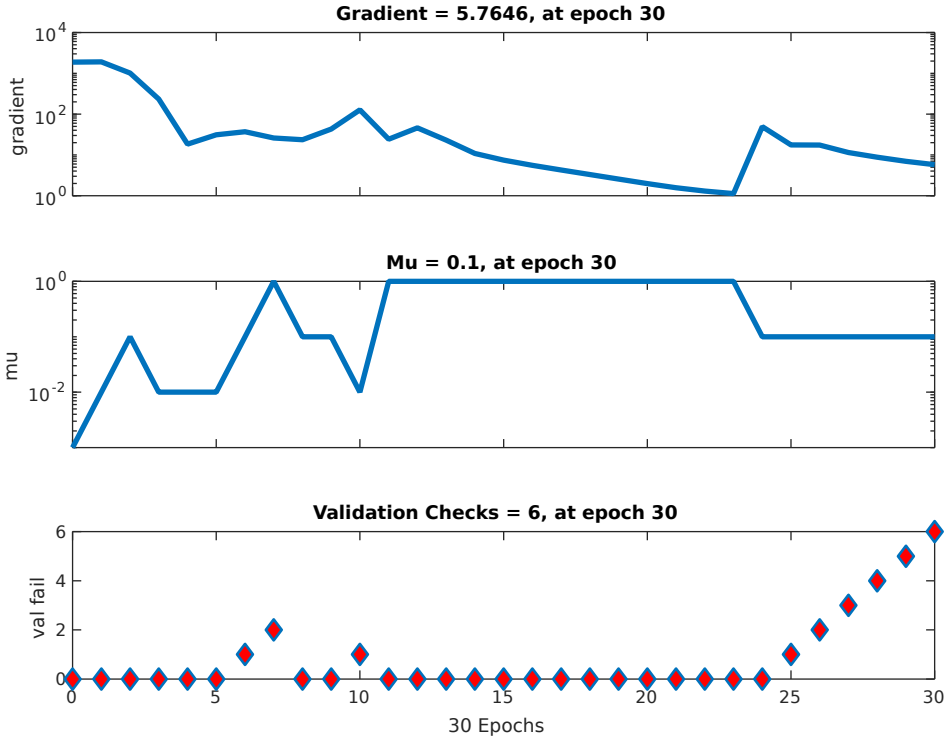



Figure 5.5.43 Different charts showing the various training parameters.

The gradient chart shows that the steps needed to reach the goal gets smaller, which is the expected outcome.

The mu chart measures how near to the newton's method the analysis would be. A high mu would create the algorithm be equivalent to gradient descent with little steps, whereas a small mu would create the algorithm be nearer to newton's method. it is useful to induce to Newton's method as quickly as attainable since it is quicker and is more accurate

close to an error minimum. Thus, mu is shrunken after every successful step (reduction in performance function) and is augmented only if a tentative step would increase the performance function. in this approach, the performance function is always reduced at every iteration of the algorithm.

The validation checks show the accumulated amount of validation checks failed in a row. The chart looks as expected since the six failures of each epoch to increase the performance on the validation test caused the test to be finished.

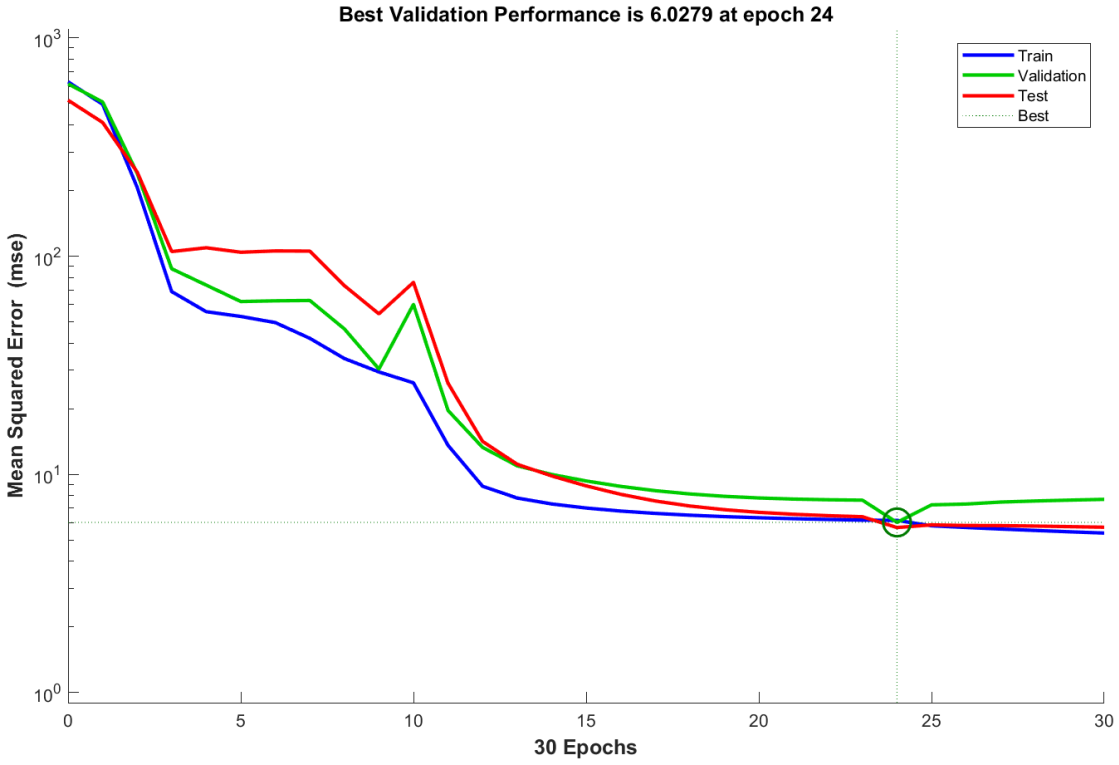


Figure 5.5.44 Performance (Mean squared error) for each of the epochs or train, validation, and test.

The Figure above shows that the neural network is improving. I also show that the best version of the neural network was found on epoch twenty-four.

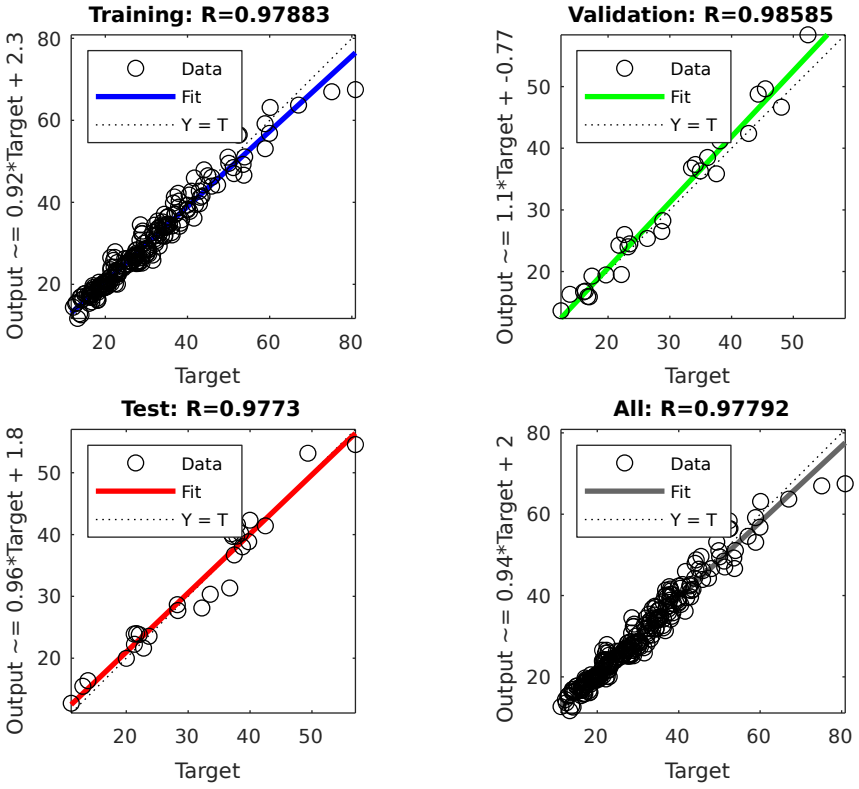



Figure 5.5.45 Charts showing the correlation between the target and the output.

The Figure above shows that the neural network is predicting well. Moreover, it demonstrates that there is much

alignment between the output of the neural network and the target value.

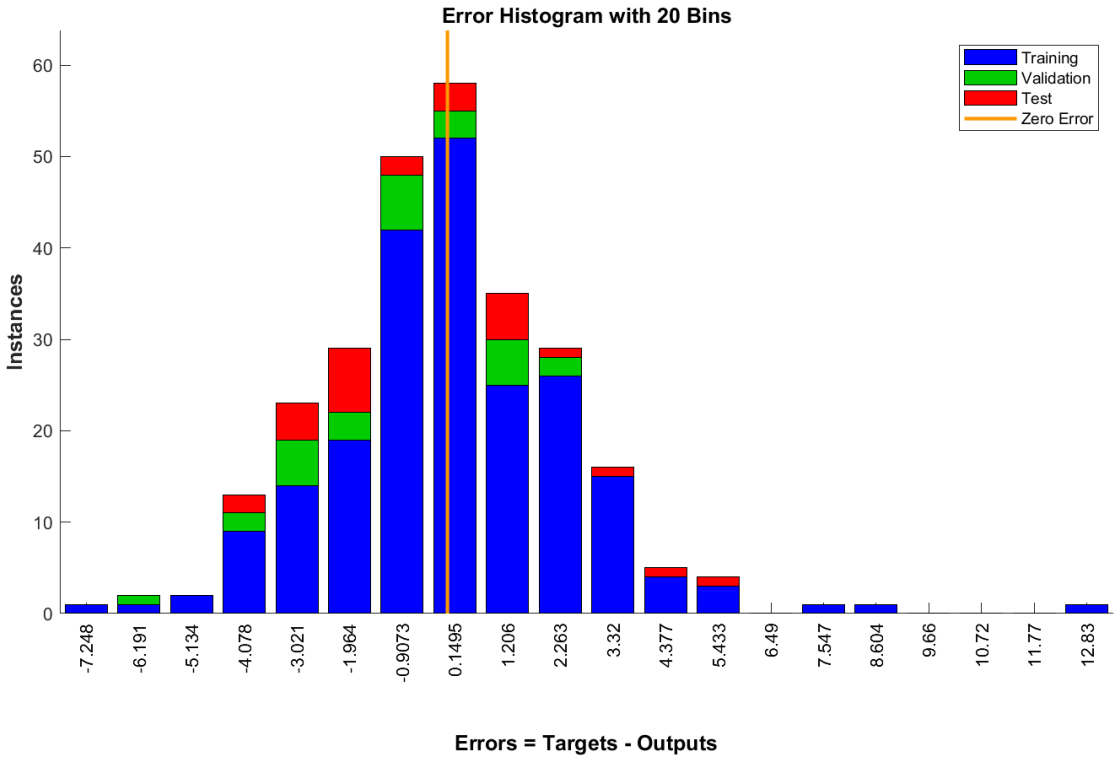



Figure 5.5.46 Error histogram of the neural network.

The error histogram mostly follows the curve expected from the neural network, namely that except for outliers, the errors follow the normal distribution. Nevertheless, the outliers show the blind spots of the model.

### V.5.3.1 Comparison between predicted values vs real values

The comparison of predicted values vs real values is used to see to what extent the predictions will align with the real data. The comparison is as follows:

Table 5.5-36 Comparison between real and predicted values when the neural network is applied to the original dataset.

| Compressive Strength (Source) | Compressive Strength (Predicted) |
|---:|---:|
| 27.25 | 27.19 |
| 29.52 | 30.04 |
| 25.93 | 25.80 |
| 30.41 | 30.81 |
| 33.2 | 32.50 |
| 29.1 | 28.22 |
| 34.52 | 34.27 |
| 37.44 | 36.70 |
| 31.96 | 32.01 |
| 39.77 | 38.85 |
| 41.68 | 45.95 |
| 38.27 | 34.92 |
| 42.86 | 42.73 |
| 45.47 | 49.64 |
| 40.53 | 37.82 |
| 45.9 | 46.12 |
| 49.34 | 53.16 |
| 43.1 | 41.22 |
| 11.117673 | 12.70 |
| 12.207564 | 14.43 |
| 12.382182 | 13.64 |
| 16.35327 | 16.86 |
| 16.229664 | 17.23 |
| 16.044255 | 16.70 |

| | |
|---|---|
| 19.489527 | 19.36 |
| 18.747891 | 19.36 |
| 19.183455 | 19.19 |
| 13.734 | 12.85 |
| 14.082255 | 12.58 |
| 13.254291 | 11.69 |
| 16.8732 | 16.82 |
| 16.655418 | 17.36 |
| 16.698582 | 18.13 |
| 19.314909 | 20.09 |
| 19.270764 | 19.98 |
| 19.663164 | 19.45 |
| 16.311087 | 16.81 |
| 16.35327 | 17.73 |
| 16.698582 | 15.93 |
| 20.0124 | 19.97 |
| 19.62 | 20.09 |
| 20.142873 | 20.03 |
| 22.802364 | 21.62 |
| 20.927673 | 21.56 |
| 22.671891 | 21.75 |
| 12.992364 | 15.45 |
| 12.774582 | 15.30 |
| 12.98844 | 15.50 |
| 16.044255 | 17.33 |
| 16.568109 | 17.33 |
| 15.565527 | 17.38 |
| 16.792758 | 18.61 |
| 17.178291 | 18.84 |
| 17.047818 | 18.61 |
| 13.864473 | 16.88 |
| 14.213709 | 16.20 |
| 13.821309 | 16.30 |
| 16.960509 | 15.89 |
| 16.698582 | 15.74 |
| 16.044255 | 15.39 |
| 19.445382 | 19.33 |
| 20.535273 | 20.40 |
| 18.704727 | 19.80 |

| | |
|---:|---:|
| 14.082255 | 16.94 |
| 13.821309 | 16.36 |
| 14.5188 | 16.41 |
| 18.137709 | 16.11 |
| 18.006255 | 16.63 |
| 18.180873 | 16.26 |
| 18.530109 | 19.64 |
| 19.358073 | 19.00 |
| 20.099709 | 19.29 |
| 18.485964 | 19.10 |
| 18.485964 | 19.22 |
| 19.009818 | 19.69 |
| 22.149018 | 19.51 |
| 22.933818 | 20.05 |
| 22.454109 | 20.17 |
| 24.459273 | 24.04 |
| 24.808509 | 24.85 |
| 24.546582 | 24.37 |
| 16.001091 | 17.32 |
| 15.03873 | 17.76 |
| 14.867055 | 17.71 |
| 20.666727 | 19.64 |
| 20.142873 | 19.52 |
| 19.837782 | 20.06 |
| 22.541418 | 22.93 |
| 22.671891 | 22.99 |
| 23.107455 | 22.86 |
| 17.61876 | 18.12 |
| 18.225018 | 18.12 |
| 16.785891 | 18.62 |
| 20.187018 | 20.62 |
| 21.014982 | 20.63 |
| 19.837782 | 20.62 |
| 23.238909 | 24.01 |
| 23.499855 | 24.48 |
| 23.674473 | 23.54 |
| 17.396073 | 19.26 |
| 17.003673 | 19.73 |
| 17.178291 | 19.32 |

| | |
|---|---|
| 21.320073 | 20.93 |
| 21.145455 | 21.74 |
| 21.451527 | 20.26 |
| 21.364218 | 24.15 |
| 22.671891 | 26.00 |
| 22.279491 | 26.57 |
| 18.0504 | 18.89 |
| 18.355491 | 19.23 |
| 18.4428 | 20.54 |
| 20.753055 | 20.78 |
| 20.535273 | 20.60 |
| 27.555309 | 25.07 |
| 24.3288 | 24.45 |
| 22.900464 | 25.34 |
| 24.7212 | 24.79 |
| 21.320073 | 22.25 |
| 22.10193 | 23.81 |
| 22.104873 | 24.21 |
| 26.552727 | 25.51 |
| 24.7212 | 26.28 |
| 25.549164 | 26.35 |
| 28.688364 | 26.50 |
| 28.907127 | 26.50 |
| 28.2528 | 26.50 |
| 22.9554 | 22.42 |
| 22.933818 | 22.68 |
| 23.2497 | 22.62 |
| 26.35947 | 25.36 |
| 27.118764 | 26.55 |
| 28.122327 | 27.12 |
| 28.2528 | 28.66 |
| 27.380691 | 28.22 |
| 27.598473 | 28.44 |
| 22.497273 | 23.35 |
| 22.236327 | 22.57 |
| 22.933818 | 23.35 |
| 28.6452 | 25.65 |
| 28.035018 | 25.10 |
| 27.555309 | 25.30 |

| | |
|---:|---:|
| 29.865564 | 28.60 |
| 30.476727 | 28.45 |
| 30.6072 | 27.43 |
| 28.122327 | 25.40 |
| 27.380691 | 26.45 |
| 26.813673 | 26.80 |
| 31.566618 | 25.89 |
| 32.219964 | 28.11 |
| 31.479309 | 27.16 |
| 35.141382 | 34.16 |
| 34.793127 | 33.91 |
| 34.094655 | 33.83 |
| 21.276909 | 23.90 |
| 21.669309 | 23.97 |
| 21.320073 | 23.57 |
| 26.203491 | 25.47 |
| 25.767927 | 24.92 |
| 25.811091 | 25.54 |
| 32.351418 | 30.67 |
| 32.219964 | 29.99 |
| 31.740255 | 31.68 |
| 21.756618 | 24.27 |
| 21.320073 | 26.56 |
| 22.017564 | 25.85 |
| 28.340109 | 27.71 |
| 27.642618 | 27.64 |
| 26.508582 | 26.56 |
| 28.427418 | 30.80 |
| 28.950291 | 32.44 |
| 28.862982 | 32.36 |
| 27.293382 | 26.85 |
| 27.423855 | 27.06 |
| 27.773091 | 25.65 |
| 33.571782 | 30.34 |
| 32.089491 | 31.10 |
| 34.400727 | 31.73 |
| 34.1388 | 37.37 |
| 32.743818 | 35.44 |
| 34.356582 | 37.11 |

| | |
|---:|---:|
| 29.080764 | 27.01 |
| 30.159864 | 27.59 |
| 28.862982 | 28.25 |
| 36.1008 | 32.62 |
| 36.710982 | 31.36 |
| 36.231273 | 32.06 |
| 37.800873 | 38.84 |
| 37.190691 | 39.70 |
| 37.975491 | 40.31 |
| 30.170655 | 28.81 |
| 30.6072 | 28.51 |
| 30.084327 | 28.51 |
| 38.018655 | 34.19 |
| 34.618509 | 33.94 |
| 36.275418 | 34.27 |
| 36.580509 | 39.83 |
| 36.798291 | 41.32 |
| 37.845018 | 39.74 |
| 39.92277992 | 39.33 |
| 36.96911197 | 37.16 |
| 35 | 36.37 |
| 32.97297297 | 33.74 |
| 32.97297297 | 33.30 |
| 38.47490347 | 40.22 |
| 36.96911197 | 40.12 |
| 35.17374517 | 34.71 |
| 34.47876448 | 31.93 |
| 42.47104247 | 41.42 |
| 39.98069498 | 38.39 |
| 36.96911197 | 37.03 |
| 34.94208494 | 36.31 |
| 33.95752896 | 34.49 |
| 39.98069498 | 42.32 |
| 37.95366795 | 41.59 |
| 37.54826255 | 37.51 |
| 34.94208494 | 34.59 |
| 43.51351351 | 41.53 |
| 41.94980695 | 39.49 |
| 39.98069498 | 38.17 |

| | |
|---:|---:|
| 35.34749035 | 36.57 |
| 35.57915058 | 34.60 |
| 42.76061776 | 42.39 |
| 40.96525097 | 42.73 |
| 38.76447876 | 38.03 |
| 37.54826255 | 35.85 |
| 52.30252596 | 56.40 |
| 47.3033537 | 44.29 |
| 58.90143334 | 53.10 |
| 49.70295638 | 57.48 |
| 43.90391656 | 44.24 |
| 38.10487674 | 41.18 |
| 53.70229419 | 46.64 |
| 44.30385034 | 48.78 |
| 36.10520784 | 38.50 |
| 33.50563827 | 36.78 |
| 42.90408211 | 39.68 |
| 37.70494296 | 42.21 |
| 31.50596936 | 32.66 |
| 30.10620113 | 27.53 |
| 32.90573759 | 33.76 |
| 33.10570448 | 29.34 |
| 28.90639979 | 25.20 |
| 52.58 | 56.48 |
| 80.87 | 67.51 |
| 58.86 | 59.18 |
| 53.9 | 51.09 |
| 60.11 | 63.14 |
| 75.11 | 66.98 |
| 67.01 | 63.72 |
| 50.05 | 49.53 |
| 44.02 | 47.92 |
| 52.37 | 58.40 |
| 49.85 | 51.04 |
| 51.3 | 47.03 |
| 40.41 | 41.79 |
| 44.95 | 46.49 |
| 41.57 | 36.16 |
| 28.52 | 34.55 |

| | |
|---:|---:|
| 29.08 | 32.99 |
| 45.87 | 43.96 |
| 53.53 | 49.25 |
| 31.97 | 34.45 |
| 48.07 | 46.65 |
| 57.02 | 54.57 |
| 33.97 | 35.23 |
| 51.14 | 48.49 |
| 59.93 | 56.83 |
| 22.39 | 27.97 |
| 33.63 | 31.84 |
| 38.55 | 35.75 |

It could be seen that there are some differences between the real value and the predicted value.

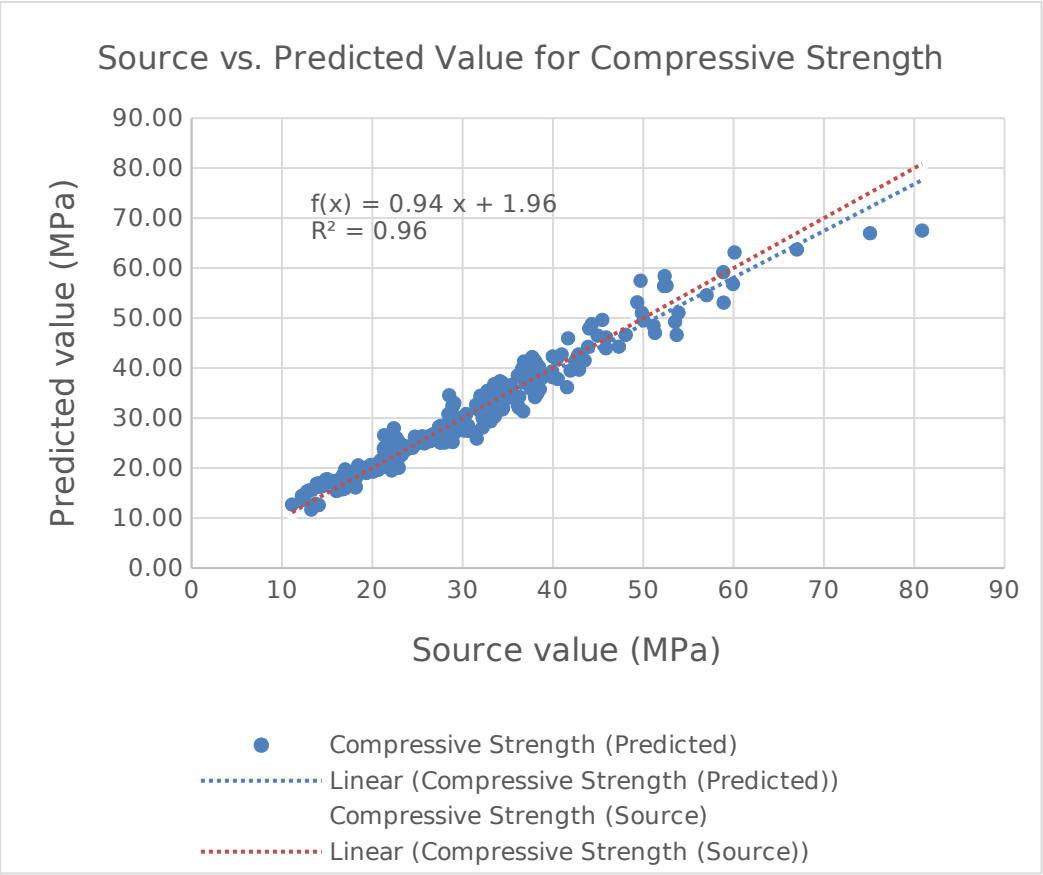



Figure 5.5.47 Source vs. Predicted Value for Compressive Strength

The chart would confirm the extent of similarity between the source value and the predicted value. The comparison between the y=x trendline also highlights the difference between the real and predicted values. The graph also shows the areas where the outliers are.

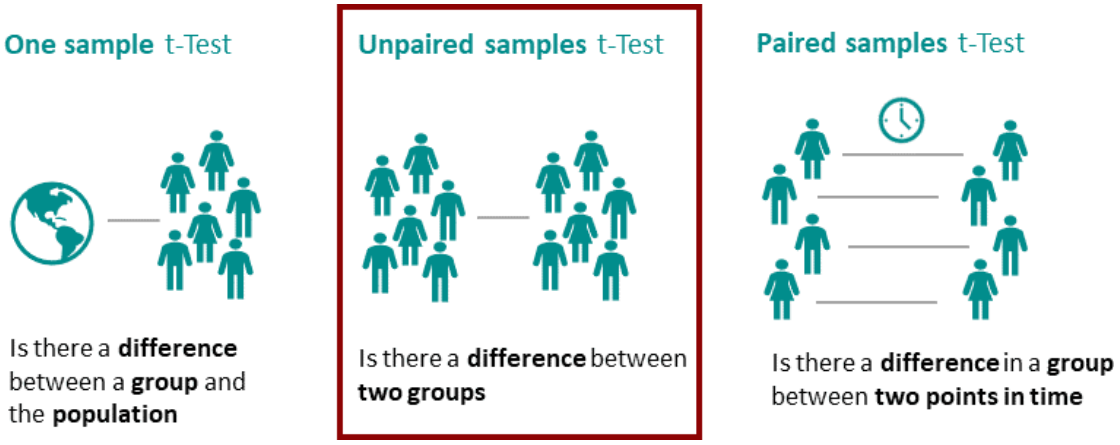

One sample t-Test
Is there a difference between a group and the population
Unpaired samples t-Test
Is there a difference between two groups
Paired samples t-Test
Is there a difference in a group between two points in time

Figure 5.5.48 Different kinds of t-test (DATAtab Team, 2022)

From the figure above it can be seen that an unpaired samples t-test would be the t-test that would be most appropriate when looking at the difference between two groups. We are eager to see the difference between the real values and the values from the model to determine if the model is sufficiently similar.

Table 5.5-37 Comparison between real and predicted values when the neural network is applied to the original dataset.

| | *Compressive Strength (Source)* | *Compressive Strength (Predicted)* |
|---|---|---|
| Mean | 29.41937114 | 29.47589941 |
| Variance | 138.6808975 | 126.8699962 |
| Observations | 270 | 270 |
| Hypothesized Mean Difference | 0 | |
| df | 537 | |
| t Stat | -0.056999846 | |
| P(T<=t) one-tail | 0.47728326 | |

| | | |
|---|---|---|
| t Critical one-tail | 1.647696117 | |
| P(T<=t) two-tail | 0.95456652 | |
| t Critical two-tail | 1.964391426 | |

From the table above, the P(T<=t) is greater than 0.05 for both one-tail and two-tail. This would indicate that the predictions are sufficiently similar with the real values. The predictions, however, are only sufficiently accurate for the 10-42 MPa range. This could be seen as the values above 42 MPa are scarce.

#### V.5.3.2 Tweaked neural network constants

The original functionality of the code that was derived would be attained by replacing the neural network constants written in section III.1.3.1 with the neural network constants below. This is possible since the neural network constants are the only thing that changed between different models and iterations.

```
%
% Auto-generated by MATLAB, 17-Jul-2022 23:44:26.
%
% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.keep = [1 2 3 4 5 6 8 9 10 11 13 14 15 18 19 20];
x1_step2.xoffset =
[0;0;0;0;0;35;1285.5;0;0;0;0;0;0;0;14;2.93890080756283];
x1_step2.gain =
[0.00389105058365759;0.00155038759689922;0.00173897921919
833;0.00306748466257669;0.00243902439024390;0.008264462809
```

```
91736;0.00177856825255669;0.00607164541590771;0.004;0.0097
799511002445;0.0192492781520693;0.00579206487112656;0.004
;0.571428571428571;0.0526868947757209;0.869905920796697];
x1_step2.ymin = -1;

% Layer 1
b1 = -0.709239974260890138 07;
IW1_1 = [0.021014363643190939 19 -0.326803997001416157 71 -
0.353757520656564627 97 -0.177999970681524677 38 -
0.232459027046472116 45 0.151103076867594304 79
0.358882842221738329 6 -0.118079441648961239 18 -
0.008405623100206489 8949 -0.097885869070403835 89
0.209623623819381876 83 0.028691738122860604 987 -
0.218731830932287235 61 0.362844900999798825 05
0.281800626530676889 82 0.190395591700141558 76];

% Layer 2
b2 = 0.201075152427956121 98;
LW2_1 = 1.594985355110133618;

% Output 1
y1_step1.ymin = -1;
y1_step1.gain = 0.0286728785406686;
y1_step1.xoffset = 11.117673;
```

## V.6 Using important DT Factors only

### *V.6.1 Linear Regression*

Linear regression is used here since it is the most intuitive method by which a data analysis could be understood. Linear regression is of form $y=\beta_0+\sum_{i=1}^{n}\beta_i x_i$, which makes it very intuitive to understand and use.

Table 5.6-38 Result using linear regression.

| | Estimate | SE | tStat | pValue |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| (Intercept) | -31.703 | 19.21 | -1.6504 | 1.01E-01 |
| Cementkgm3 | 0.1306 | 0.0143 | 9.1333 | 2.15E-16 |
| CoarseAggregateskgm3 | -0.27654 | 0.0417 | -6.6382 | 4.26E-10 |
| FineAggregateskgm3 | -0.16893 | 0.0439 | -3.8441 | 1.72E-04 |
| CoarseRCAkgm3 | -0.27991 | 0.0416 | -6.7308 | 2.58E-10 |
| FineRCAkgm3 | 0 | 0 | NaN | NaN |
| WaterContentkgm3 | -0.74888 | 0.1194 | -6.2725 | 2.9E-09 |
| WaterToBinderRatio | 205.89 | 36.552 | 5.6328 | 7.4E-08 |
| TotalUnitWeightkgm3 | 0.1892 | 0.0402 | 4.7097 | 5.19E-06 |
| GraniteFineskgm3 | 0 | 0 | NaN | NaN |
| FlyAshContentkgm3 | 0 | 0 | NaN | NaN |
| GroundGranulatedBlastFurnaceSlagGGBSkgm3 | 0 | 0 | NaN | NaN |
| NanoSilicakgm3 | -0.55373 | 0.2124 | -2.6068 | 0.00997 |
| Fillerkgm3 | 0.1821 | 0.0661 | 2.7532 | 6.55E-03 |
| CrumbRubberkgm3 | -0.12064 | 0.0232 | -5.1994 | 5.79E-07 |
| MetakaoliniteContentkgm3 | 0 | 0 | NaN | NaN |
| polypropyleneFibreByVolume | 0 | 0 | NaN | NaN |
| dryCuring | -2.5545 | 0.8811 | -2.8992 | 0.00424 |
| Superplasticizer | 0 | 0 | NaN | NaN |
| SchmidtReboundNumber | 0 | 0 | NaN | NaN |
| UPVkms | 0 | 0 | NaN | NaN |
| AgeOfConcretedays | 0.33433 | 0.0206 | 16.237 | 3.5E-36 |

The estimate shows what the coefficient that would be attached to the factor would be. The standard error shows the variability of a coefficient. In order words, it shows how far

apart the value that would have been predicted by regression from the other values. tStat is the estimate over the standard error. The pValue is the probability of the coefficient being insignificant, with 0.05 being the p value that is the threshold whether the value would be removed. The result from the linear regression shows the importance of each of the variables and coefficient that they would add to the model. The NaN would indicate factors that do not exist within the dataset.

Table 5.6-39 Model training results

| | |
|---|---|
| RMSE (Validation) | 4.7073 |
| R-Squared (Validation) | 0.81 |
| MSE (Validation) | 22.159 |
| MAE (Validation) | 3.3749 |
| Prediction speed | ~2300 obs/sec |
| Training time | 10.679 sec |

Table 5.6-40 Model parameters

| | |
|---|---|
| Model Type | |
| Preset | |

| | |
|---|---|
| | Linear |
| Terms | Linear |
| Robust option | Off |

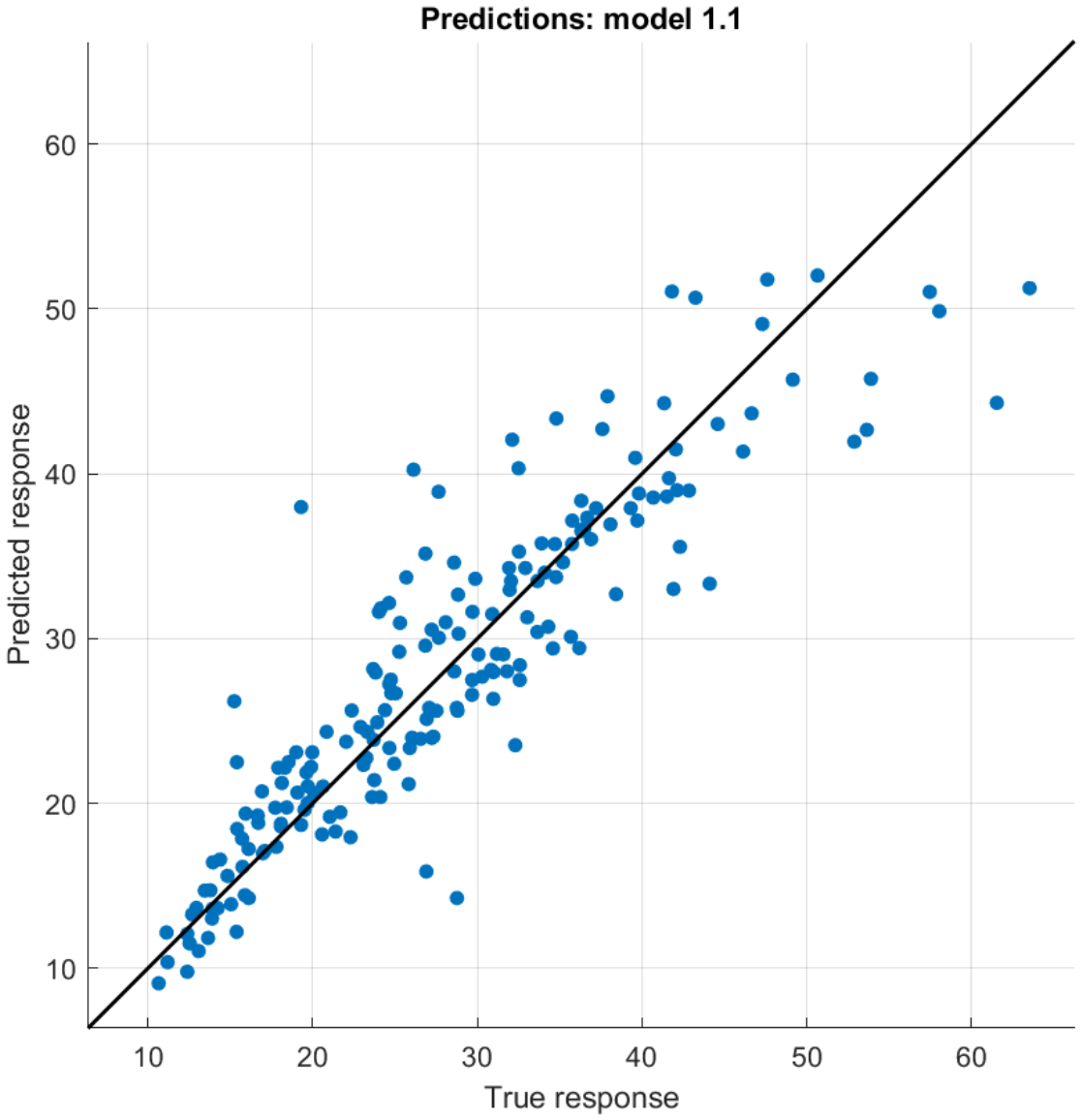



Figure 5.6.49 True vs Predicted for Linear Regression

The true vs predicted response graph shows the how

much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also shows that there are outliers and that most of the reliable data is between 10 to 45 MPa compressive strength.

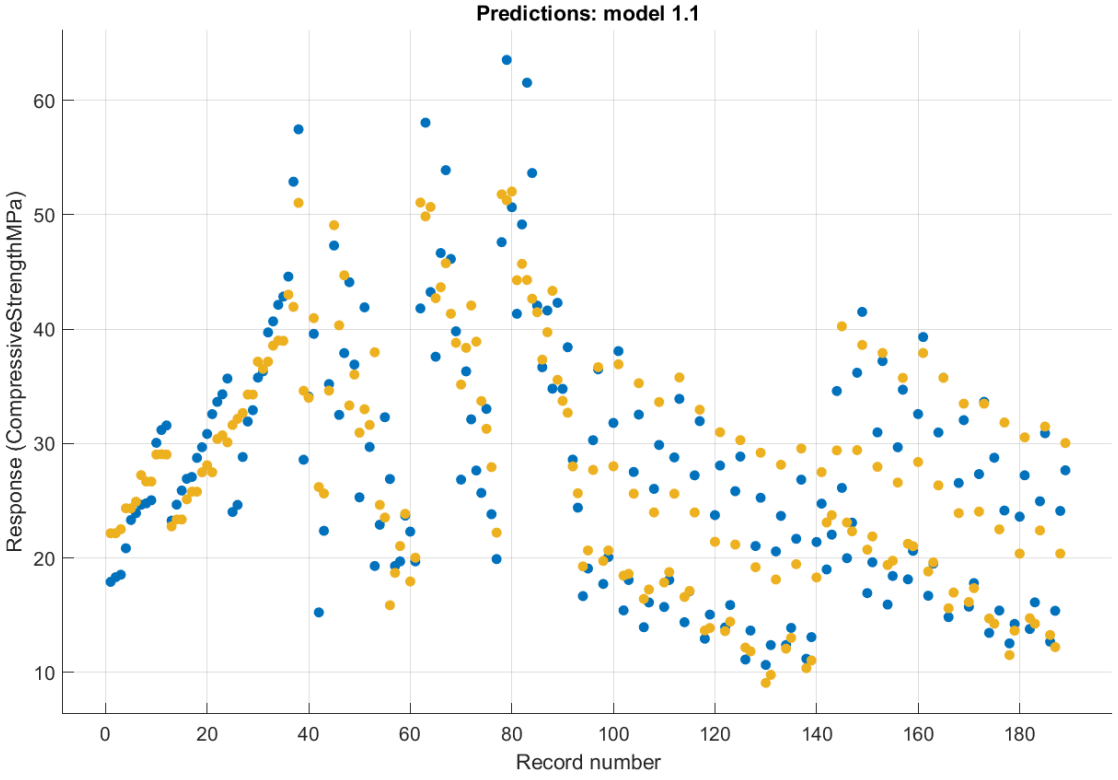



Figure 5.6.50 Response Plot for Linear Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

### *V.6.2 Matern 5/2 Gaussian Process Regression*

This part has been added to give another method by which the neural network method should be able to beat.

Table 5.6-41 Model training results

| | |
|---|---|
| RMSE (Validation) | 3.8345 |
| R-Squared (Validation) | 0.88 |
| MSE (Validation) | 14.703 |
| MAE (Validation) | 2.5386 |
| Prediction speed | ~6500 obs/sec |
| Training time | 1.1544 sec |

Table 5.6-42 Model parameters

| | |
|---|---|
| Model Type | |
| Preset | Matern 5/2 GPR |
| Basis function | Constant |
| Kernel function | Matern 5/2 |
| Use isotropic kernel | true |
| Kernel scale | Automatic |
| Signal standard deviation | Automatic |
| Sigma | Automatic |
| Standardize | true |
| Optimize numeric parameters | true |

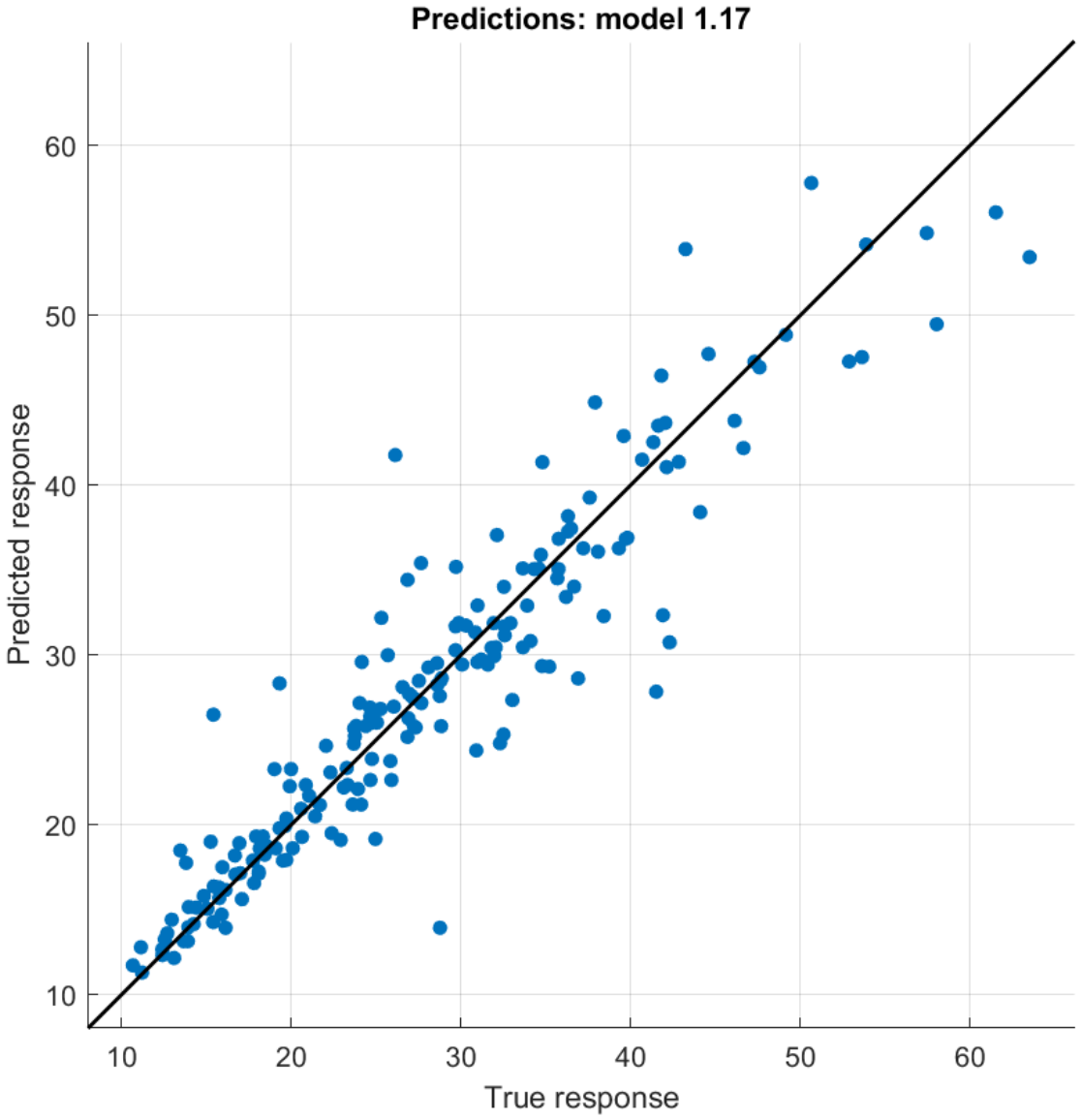



Figure 5.6.51 Predicted vs Actual for Matern 5/2 Gaussian Process Regression

The true vs predicted response graph shows the how much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also

shows that there are outliers and that most of the reliable data is between 10 to 45 MPa compressive strength.

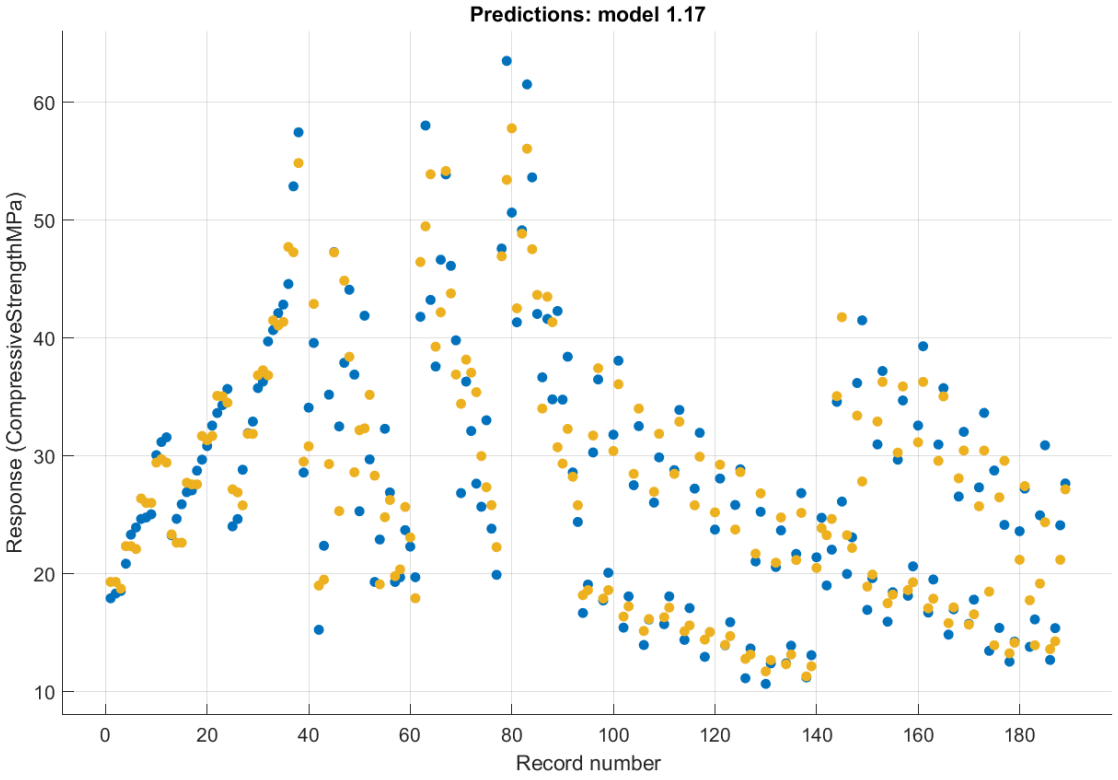



Figure 5.6.52 Response Plot for Matern 5/2 Gaussian Process Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

### *V.6.3 Tweaked neural network for important destructive testing factors*

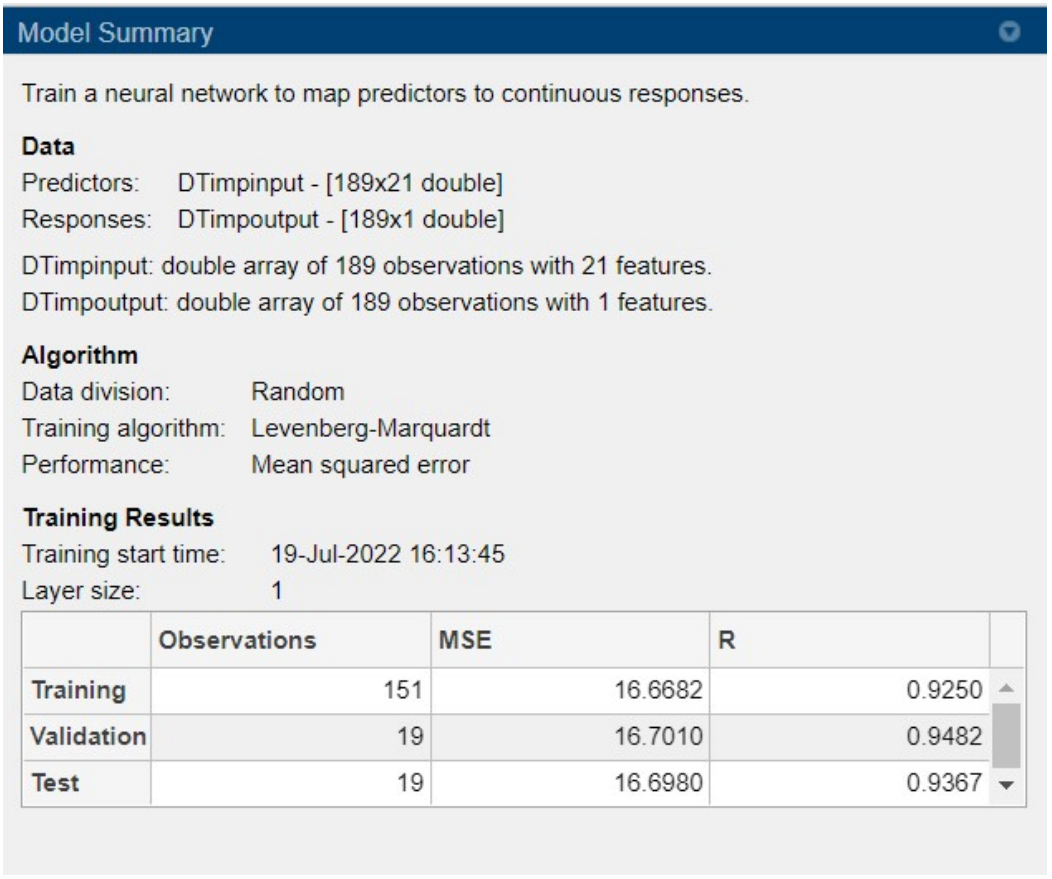

Model Summary
Train a neural network to map predictors to continuous responses.
Data
Predictors: DTimpinput - [189x21 double]
Responses: DTimpoutput - [189x1 double]
DTimpinput: double array of 189 observations with 21 features.
DTimpoutput: double array of 189 observations with 1 features.
Algorithm
Data division: Random
Training algorithm: Levenberg-Marquardt
Performance: Mean squared error
Training Results
Training start time: 19-Jul-2022 16:13:45
Layer size: 1
Observations MSE R
Training 151 16.6682 0.9250
Validation 19 16.7010 0.9482
Test 19 16.6980 0.9367

Figure 5.6.53 Model Summary.

The Figure above shows the summary of the model. The R value shown indicates that the model created is a good match to the data given. Moreover, the closeness of the mean square error between training, validation and test means that no overfitting has occurred. The test-train ratio of 80:20 is also implemented. This result is chosen since the mean squared error is lower than the value obtained using other methods, such as stepwise regression.

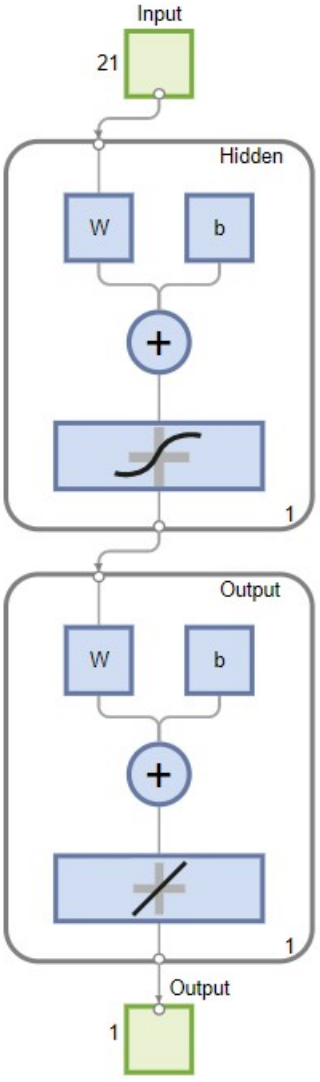



Figure 5.6.54 Diagram of the neural network.

The Figure above shows that a sigmoid activation is used. It also shows that there are twenty-one features as input and one as output. It also shows that the hidden layer

has a size of one.

**Training Results**

Training finished: Met validation criterion

**Training Progress**

| Unit | Initial Value | Stopped Value | Target Value |
|---|---|---|---|
| Epoch | 0 | 88 | 1000 |
| Elapsed Time | - | 00:00:00 | - |
| Performance | 333 | 16.7 | 0 |
| Gradient | 886 | 2.28 | 1e-07 |
| Mu | 0.001 | 0.001 | 1e+10 |
| Validation Checks | 0 | 6 | 6 |

Figure 5.6.55 Training progress with elapsed time and different stopping criteria

The Figure above shows that the machine learning run is successful. Namely, the mean squared error has decreased. This is shown under performance. The training was finished by meeting the validation criteria, which is that for six consecutive iterations, the validation error increases.

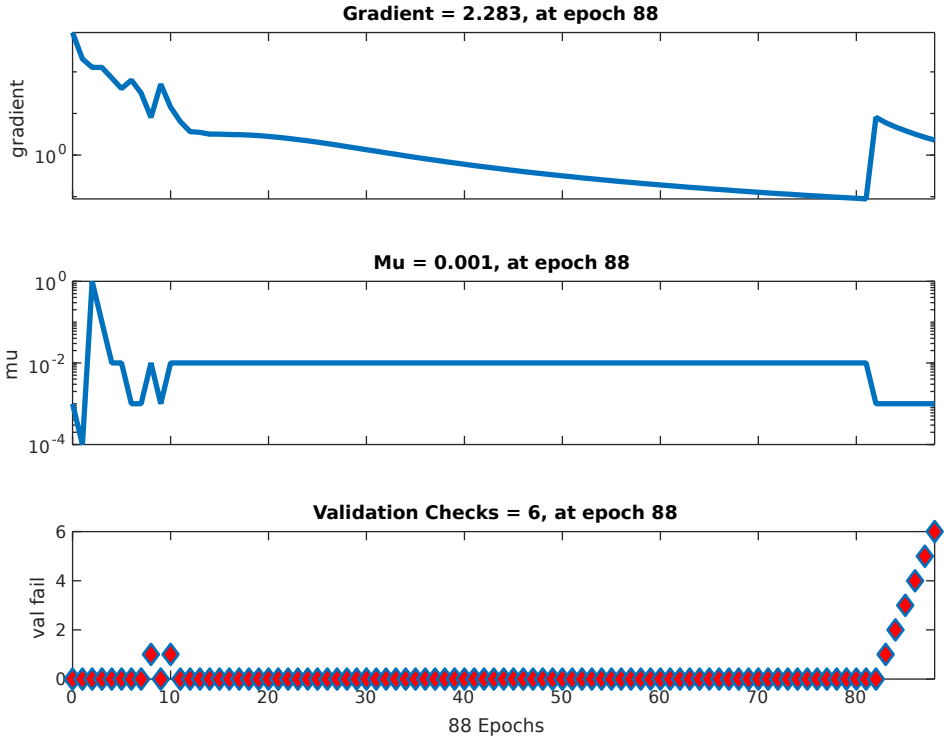



Figure 5.6.56 Different charts showing the various training parameters.

The gradient chart shows that the steps needed to reach the goal gets smaller, which is the expected outcome.

The mu chart measures how near to the newton's method the analysis would be. A high mu would create the algorithm be equivalent to gradient descent with little steps, whereas a small mu would create the algorithm be nearer to newton's method. it is useful to induce to Newton's method as quickly as attainable since it is quicker and is more accurate

close to an error minimum. Thus, mu is shrunken after every successful step (reduction in performance function) and is augmented only if a tentative step would increase the performance function. in this approach, the performance function is always reduced at every iteration of the algorithm.

The validation checks show the accumulated amount of validation checks failed in a row. The chart looks as expected since the six failures of each epoch to increase the performance on the validation test caused the test to be finished.

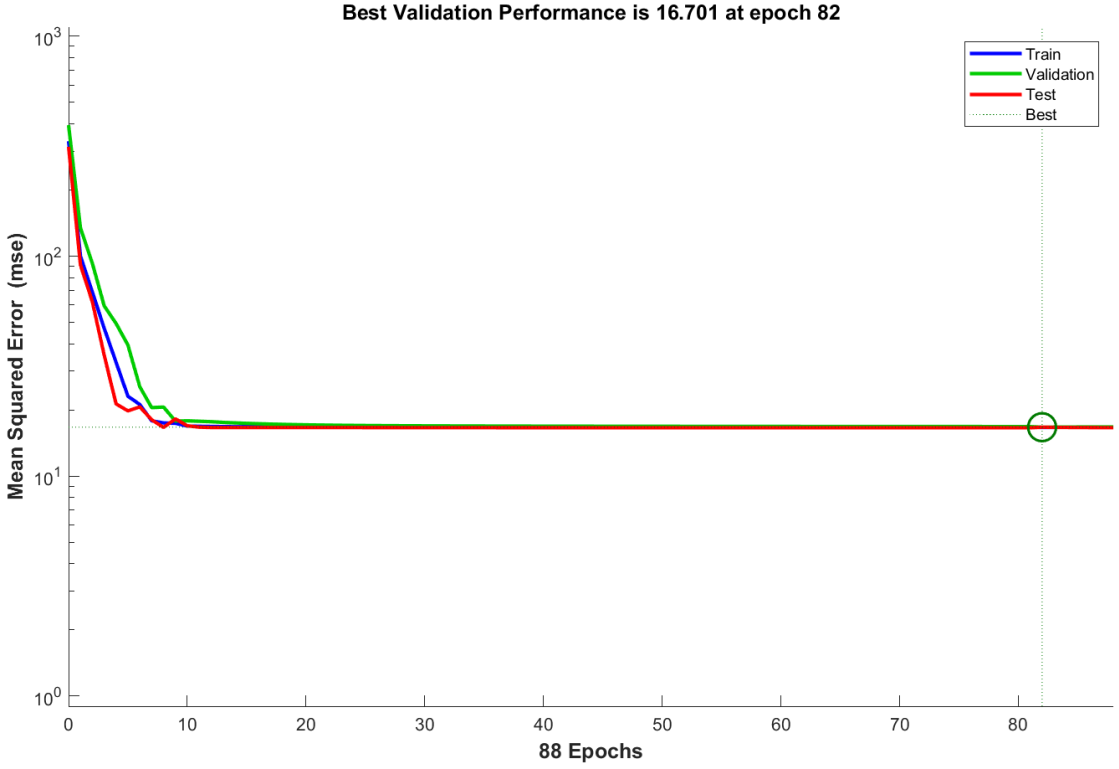



Figure 5.6.57 Performance (Mean squared error) for each of the

epochs or train, validation, and test.

The Figure above shows that the neural network is improving. I also show that the best version of the neural network was found on epoch eighty-two.

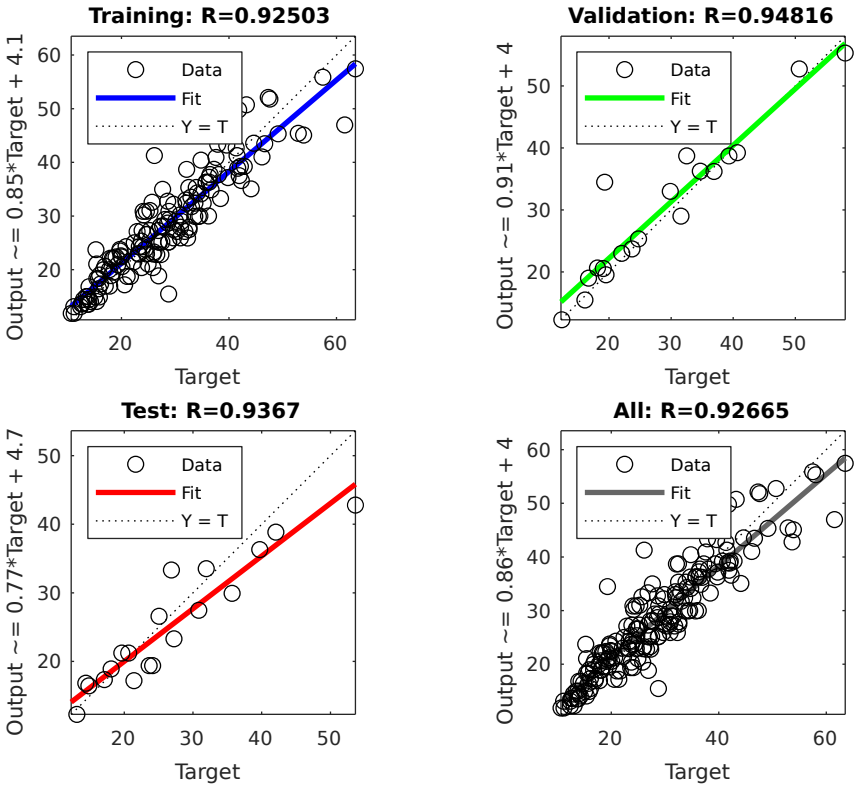



Figure 5.6.58 Charts showing the correlation between the target and the output.

The Figure above shows that the neural network is predicting well. Moreover, it demonstrates that there is much

alignment between the output of the neural network and the target value.

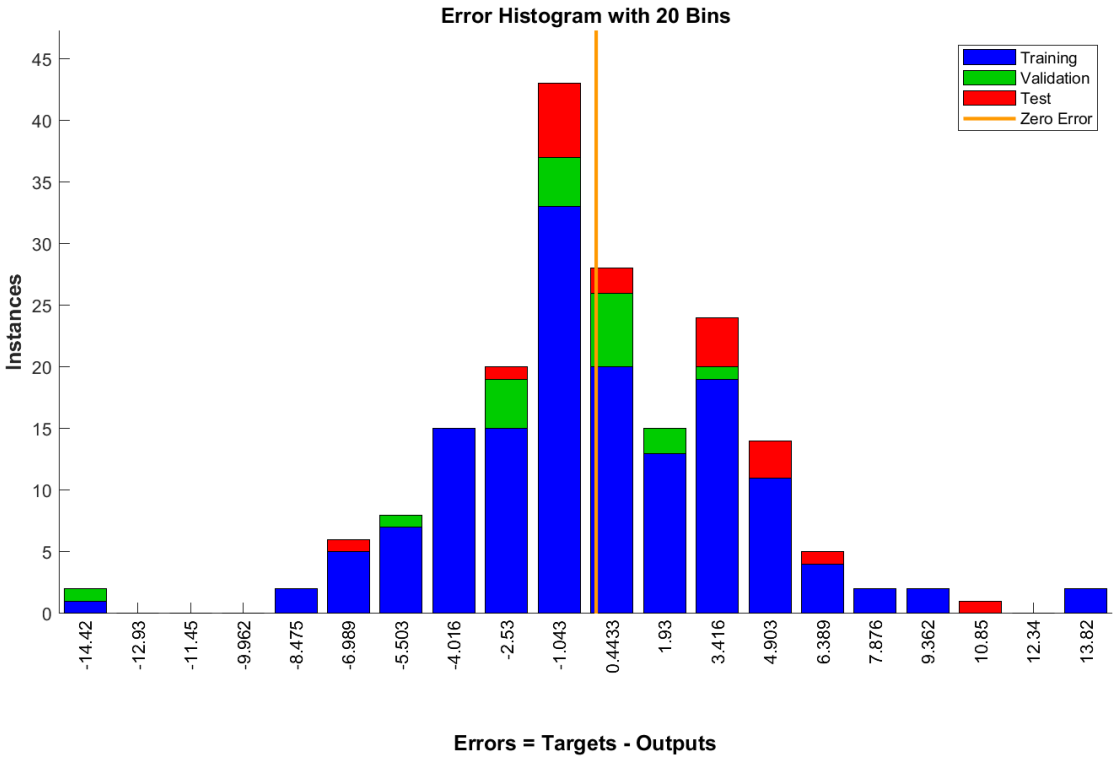



Figure 5.6.59 Error histogram of the neural network.

The error histogram mostly follows the curve expected from the neural network, namely that except for outliers, the errors follow the normal distribution. Nevertheless, the outliers show the blind spots of the model.

### V.6.3.1 Comparison between predicted values vs real values

The comparison of predicted values vs real values is used to see to what extent the predictions will align with the real data. The comparison is as follows:

Table 5.6-43 Comparison between real and predicted values when the neural network is applied to the original dataset.

| Compressive Strength (Source) | Compressive Strength (Predicted) |
|---:|---:|
| 17.92155855 | 22.13 |
| 18.3254812 | 22.13 |
| 18.54422754 | 22.13 |
| 20.8558458 | 24.29 |
| 23.32262387 | 24.29 |
| 23.9292315 | 24.29 |
| 24.65347537 | 26.58 |
| 24.77819508 | 26.58 |
| 25.05006746 | 26.58 |
| 30.07010786 | 29.00 |
| 31.18801294 | 29.00 |
| 31.5817028 | 29.00 |
| 23.26824437 | 22.91 |
| 24.66417555 | 22.91 |
| 25.89965488 | 22.91 |
| 26.92654678 | 25.12 |
| 27.0824143 | 25.12 |
| 28.75111365 | 25.12 |
| 29.68631878 | 27.46 |
| 30.84157217 | 27.46 |
| 32.57445226 | 27.46 |
| 33.64413133 | 29.92 |
| 34.30733235 | 29.92 |
| 35.68263401 | 29.92 |

| | |
|---:|---:|
| 24.02605286 | 30.86 |
| 24.64292245 | 30.86 |
| 28.82976209 | 30.86 |
| 31.93005181 | 33.52 |
| 32.91842391 | 33.52 |
| 35.76234635 | 36.31 |
| 36.31706604 | 36.31 |
| 39.7150431 | 36.31 |
| 40.67657424 | 39.24 |
| 42.12350638 | 39.24 |
| 42.8434002 | 39.24 |
| 44.59 | 43.56 |
| 52.88 | 45.41 |
| 57.46 | 55.86 |
| 28.59 | 32.75 |
| 34.1 | 34.31 |
| 39.59 | 43.22 |
| 15.25 | 23.73 |
| 22.38 | 25.00 |
| 35.2 | 32.39 |
| 47.3033537 | 52.10 |
| 32.50580381 | 38.72 |
| 37.90490985 | 43.37 |
| 44.10388345 | 35.06 |
| 36.9050754 | 36.20 |
| 25.30699576 | 31.01 |
| 41.90424766 | 37.52 |
| 29.70626735 | 32.19 |
| 19.30798905 | 34.47 |
| 22.90739308 | 27.10 |
| 32.30583692 | 25.90 |
| 26.90673088 | 18.85 |
| 19.30798905 | 20.92 |
| 19.70792283 | 23.48 |
| 23.70726064 | 23.71 |
| 22.30749241 | 21.46 |
| 19.70792283 | 23.77 |
| 41.81 | 49.79 |
| 58.04 | 55.32 |

| | |
|---:|---:|
| 43.24 | 50.73 |
| 37.59 | 40.91 |
| 46.65 | 43.47 |
| 53.89 | 45.08 |
| 46.13 | 41.01 |
| 39.81 | 37.16 |
| 26.85 | 33.32 |
| 36.31 | 37.22 |
| 32.12 | 38.69 |
| 27.65 | 34.98 |
| 25.69 | 32.56 |
| 33.03 | 31.74 |
| 23.83 | 27.30 |
| 19.91 | 22.57 |
| 47.6 | 51.79 |
| 63.52 | 57.43 |
| 50.65 | 52.74 |
| 41.34 | 42.69 |
| 49.15 | 45.32 |
| 61.53 | 46.97 |
| 53.64 | 42.79 |
| 42.05 | 38.85 |
| 36.67 | 34.89 |
| 41.63 | 38.90 |
| 34.8 | 40.41 |
| 42.3 | 36.60 |
| 34.78 | 34.11 |
| 38.42 | 33.26 |
| 28.6 | 28.69 |
| 24.4 | 23.81 |
| 16.67408745 | 19.98 |
| 19.08407654 | 20.55 |
| 30.29733684 | 27.12 |
| 36.48917792 | 37.73 |
| 17.73729623 | 19.98 |
| 20.08714893 | 20.55 |
| 31.80401899 | 27.12 |
| 38.08091366 | 37.73 |
| 15.42997543 | 18.36 |

| | |
|---|---|
| 18.08353808 | 18.90 |
| 27.51842752 | 25.16 |
| 32.53071253 | 35.31 |
| 13.95577396 | 16.82 |
| 16.11793612 | 17.34 |
| 26.04422604 | 23.29 |
| 29.87714988 | 32.99 |
| 15.72481572 | 18.36 |
| 18.08353808 | 18.90 |
| 28.7960688 | 25.16 |
| 33.90663391 | 35.31 |
| 14.39465479 | 16.82 |
| 17.08939061 | 17.34 |
| 27.22693625 | 23.29 |
| 31.96262869 | 32.99 |
| 12.95510303 | 14.45 |
| 15.06037891 | 14.92 |
| 23.74888792 | 20.38 |
| 28.08480194 | 29.36 |
| 13.93592784 | 14.45 |
| 15.89423096 | 14.92 |
| 25.83911346 | 20.38 |
| 28.86736346 | 29.36 |
| 11.13628718 | 13.12 |
| 13.66187707 | 13.56 |
| 21.05146811 | 18.75 |
| 25.26478927 | 27.30 |
| 10.66221347 | 11.85 |
| 12.39728002 | 12.27 |
| 20.57691384 | 17.19 |
| 23.68422317 | 25.33 |
| 12.40136479 | 13.12 |
| 13.89927435 | 13.56 |
| 21.68388678 | 18.75 |
| 26.84607622 | 27.30 |
| 11.20086269 | 11.85 |
| 13.09100365 | 12.27 |
| 21.40176799 | 17.19 |
| 24.75357757 | 25.33 |

| | |
|---:|---:|
| 19.00752454 | 22.38 |
| 22.04656081 | 22.99 |
| 34.59229666 | 30.01 |
| 26.12922092 | 41.27 |
| 19.98563305 | 22.38 |
| 23.09298341 | 22.99 |
| 36.19115808 | 30.01 |
| 41.50767557 | 41.27 |
| 16.9375 | 20.64 |
| 19.63282967 | 21.22 |
| 30.98008242 | 27.91 |
| 37.2103022 | 38.71 |
| 15.9375 | 18.99 |
| 18.43282967 | 19.54 |
| 29.68035714 | 25.92 |
| 34.71057692 | 36.25 |
| 18.1375 | 20.64 |
| 20.63255495 | 21.22 |
| 32.58008242 | 27.91 |
| 39.31057692 | 38.71 |
| 16.70655199 | 18.99 |
| 19.51466629 | 19.54 |
| 30.97222706 | 25.92 |
| 35.7525599 | 36.25 |
| 14.83978931 | 16.43 |
| 16.98687872 | 16.94 |
| 26.55697493 | 22.81 |
| 32.04692985 | 32.40 |
| 15.75112086 | 16.43 |
| 17.8075247 | 16.94 |
| 27.33256875 | 22.81 |
| 33.65120781 | 32.40 |
| 13.46266875 | 14.99 |
| 28.76499645 | 15.47 |
| 15.41032044 | 21.05 |
| 24.15249252 | 30.20 |
| 12.54481036 | 13.63 |
| 14.24440116 | 14.08 |
| 23.61437592 | 19.38 |

| | |
|---|---|
| 27.22875185 | 28.10 |
| 13.80041575 | 14.99 |
| 16.12780923 | 15.47 |
| 24.9596674 | 21.05 |
| 30.90614337 | 30.20 |
| 12.69039095 | 13.63 |
| 15.39102456 | 14.08 |
| 24.11875839 | 19.38 |
| 27.66379635 | 28.10 |

It could be seen that there are some differences between the real value and the predicted value.

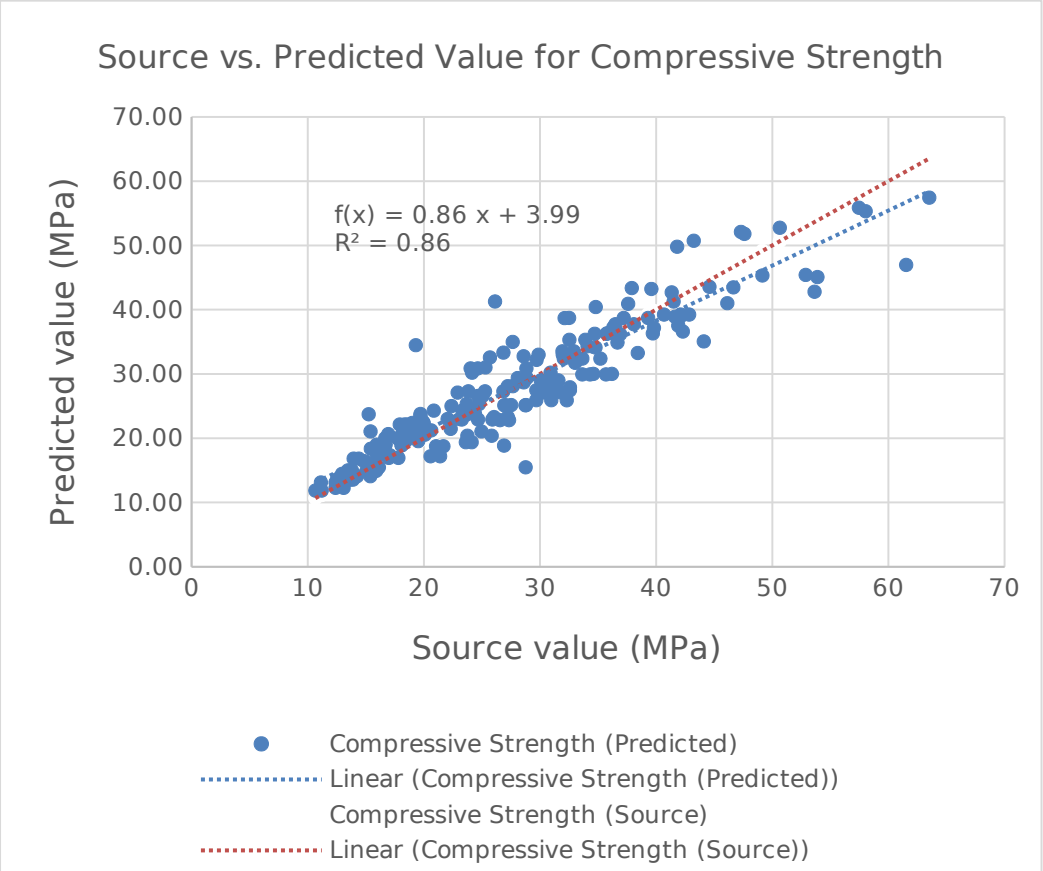



Figure 5.6.60 Source vs. Predicted Value for Compressive Strength

The chart would confirm the extent of similarity between the source value and the predicted value. The comparison between the y=x trendline also highlights the difference between the real and predicted values. The graph also shows the areas where the outliers are.

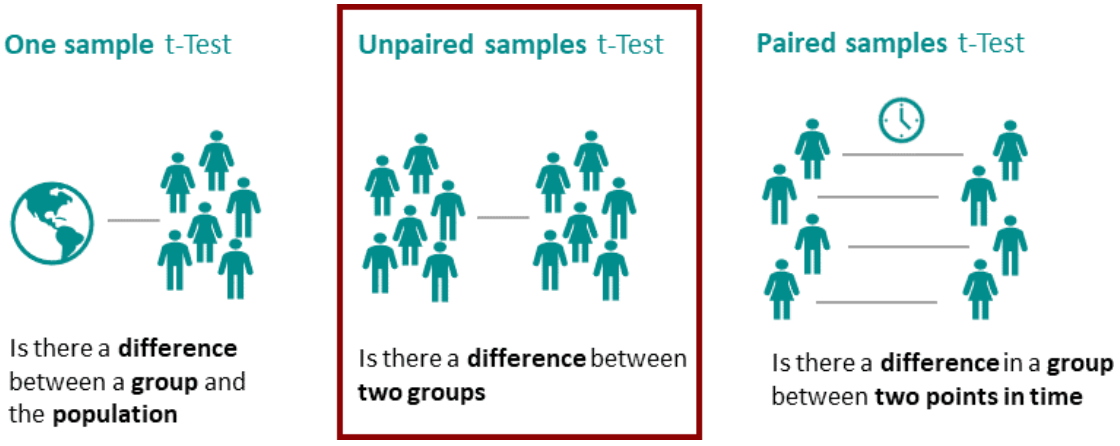

One sample t-Test
Is there a difference between a group and the population
Unpaired samples t-Test
Is there a difference between two groups
Paired samples t-Test
Is there a difference in a group between two points in time

Figure 5.6.61 Different kinds of t-test (DATAtab Team, 2022)

From the figure above it can be seen that an unpaired samples t-test would be the t-test that would be most appropriate when looking at the difference between two groups. We are eager to see the difference between the real values and the values from the model to determine if the model is sufficiently similar.

Table 5.6-44 Comparison between real and predicted values when the neural network is applied to the original dataset.

| | *Compressive Strength (Source)* | *Compressive Strength (Predicted)* |
|---|---|---|
| Mean | 28.1145082 | 28.08636995 |
| Variance | 118.609677 | 101.4856381 |
| Observations | 189 | 189 |
| Hypothesized Mean Difference | 0 | |
| df | 374 | |
| t Stat | 0.026074896 | |
| P(T<=t) one-tail | 0.489605754 | |
| t Critical one-tail | 1.648938048 | |
| P(T<=t) two-tail | 0.979211507 | |
| t Critical two-tail | 1.966327183 | |

From the table above, the P(T<=t) is greater than 0.05 for both one-tail and two-tail. This would indicate that the predictions are sufficiently similar with the real values. The predictions, however, are only sufficiently accurate for the 10-42 MPa range. This could be seen as the values above 42 MPa are scarce.

### V.6.3.2 Tweaked neural network constants

The original functionality of the code that was derived would be attained by replacing the neural network constants written in section III.1.3.1 with the neural network constants below. This is possible since the neural network constants are the only thing that changed between different models and iterations.

%

```
% Auto-generated by MATLAB, 19-Jul-2022 18:29:40.
%
% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.keep = [1 2 3 4 6 7 8 12 13 14 17 21];
x1_step2.xoffset = [134.6;0;362.5;0;96.9;0.33;1565.35;0;0;0;0;3];
x1_step2.gain =
[0.00534188034188034;0.0020242914979757;0.00253936008125
952;0.0020242914979757;0.013783597518952;9.090909090909
09;0.00240196961508437;0.248138957816377;0.01924927815206
93;0.00579206487112656;2;0.0377358490566038];
x1_step2.ymin = -1;

% Layer 1
b1 = 2.302140765828768032;
IW1_1 = [-0.31533317935786236985 2.2508091525668518784
1.1481664070351866869 2.2843975706989354535
0.87196893897494165415 -0.33551562597463419069 -
1.3430977212752601702 0.033147344578491416689 -
0.11872370855297048609 0.33073310313458315068
0.023387019977093425477 -0.15083317021764827692];

% Layer 2
b2 = 2.6511954162786981 47;
LW2_1 = -4.3640756352169178811;

% Output 1
y1_step1.ymin = -1;
y1_step1.gain = 0.0378373770662546;
y1_step1.xoffset = 10.6622134653275;
```

## V.7 Summary of the mean squared error of different analysis techniques

The tables would give that there are differences once the prediction has been stripped of the factors that are deemed unimportant. The lower MSE of the NDT test might be caused by higher amount of data and the regularity of the

data.

Table 5.7-45 Breakdown of different regression techniques

| Predictive model | R-Squared | Mean Squared Error |
|---|---|---|
| Non-destructive factors | | |
| Linear Regression | 0.95 | 7.4013 |
| Stepwise Quadratic Regression with Interactions | 0.94 | 8.8826 |
| Exponential Gaussian Process Regression | 0.96 | 4.9318 |
| Untweaked neural network | 0.93 | 9.3106 |
| Tweaked neural network | 0.986 | 4.6667 |
| Destructive factors | | |
| Linear Regression | 0.83 | 20.86 |
| Rational Quadratic Gaussian Process Regression | 0.89 | 13.598 |
| Tweaked neural network | 0.9523 | 10.9439 |
| Important NDT factors only | | |
| Linear Regression | 0.95 | 7.5425 |
| Stepwise Quadratic Regression with Interactions | 0.95 | 6.7388 |
| Tweaked neural network | 0.9788 | 6.1599 |
| Important DT factors only | | |
| Linear Regression | 0.81 | 22.159 |
| Matern 5/2 Gaussian Process Regression | 0.88 | 14.703 |
| Tweaked neural network | 0.925 | 16.701 |

Table 5.7-46 Comparison between including all factors and including only important factors.

| Predictive model | R-Squared | Mean Squared Error |
|---|---|---|

| | | |
|---|---|---|
| Non-destructive factors | | |
| All factors (Tweaked neural network) | 0.986 | 4.6667 |
| Important Factors (Tweaked neural network) | 0.9788 | 6.1599 |
| Destructive factors | | |
| All Factors (Tweaked neural network) | 0.9523 | 10.9439 |
| Important Factors (Tweaked neural network) | 0.925 | 16.701 |

## V.8 Discussion

Linear regression has successfully been used as a sanity check. The most successful non-NN algorithm, stepwise quadratic regression with interactions was also featured. The repeatability of the results is also a matter of interest since the neural network also changes rapidly even without changing the neural network parameters.

The neural network, when tweaked, was also able to give a performance better than the other methods. The tweaking is concerned with the changing of the size of the hidden layer. The hidden layer is modified so that the difference between the mean squared error (MSE) of the test set and the validation set would be small while obtaining a model with a MSE on the validation set lower than the best model tested.

The generic All – Train all available model types was

used. The Train all option uses different models which could be categorized as: linear regression models, regression trees, support vector machines, gaussian process regression models, ensembles of trees and neural networks.

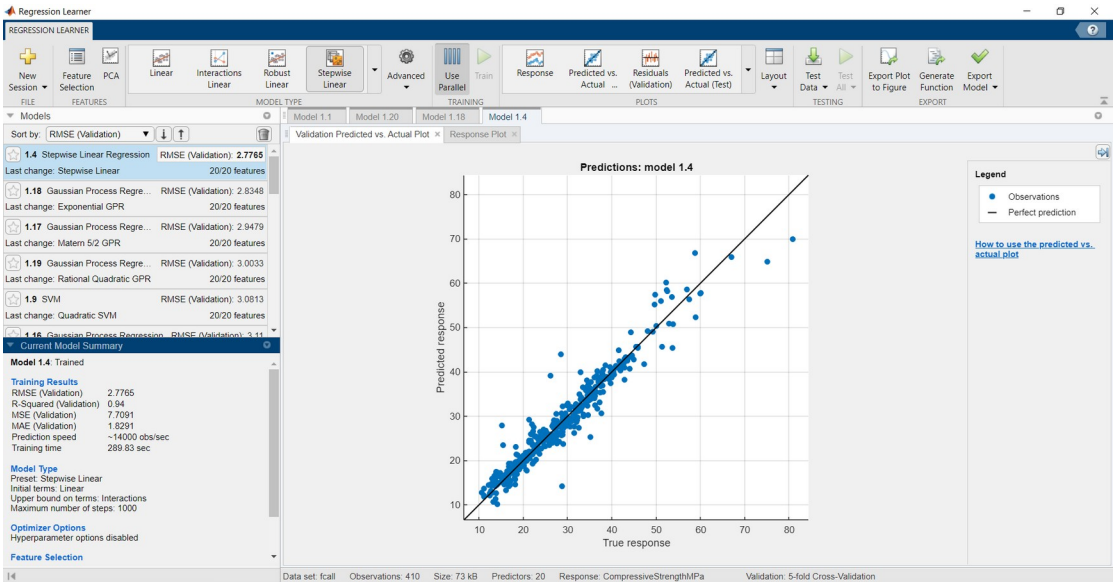



Figure 5.8.62 Different Models are used in the analysis.

The models are made to run (using parallel to make the analysis run faster) then afterwards, the models are ranked based on the root mean squared error (RMSE) in the validation set. The RMSE is used since it measures how accurate the model would be.

Primary Component Analysis (PCA) could be added by choosing the PCA icon under regression learner then choosing the advanced PCA options. The default option of filtering by

variance explained is sufficient since the simplified model would be desired when performing PCA analysis.

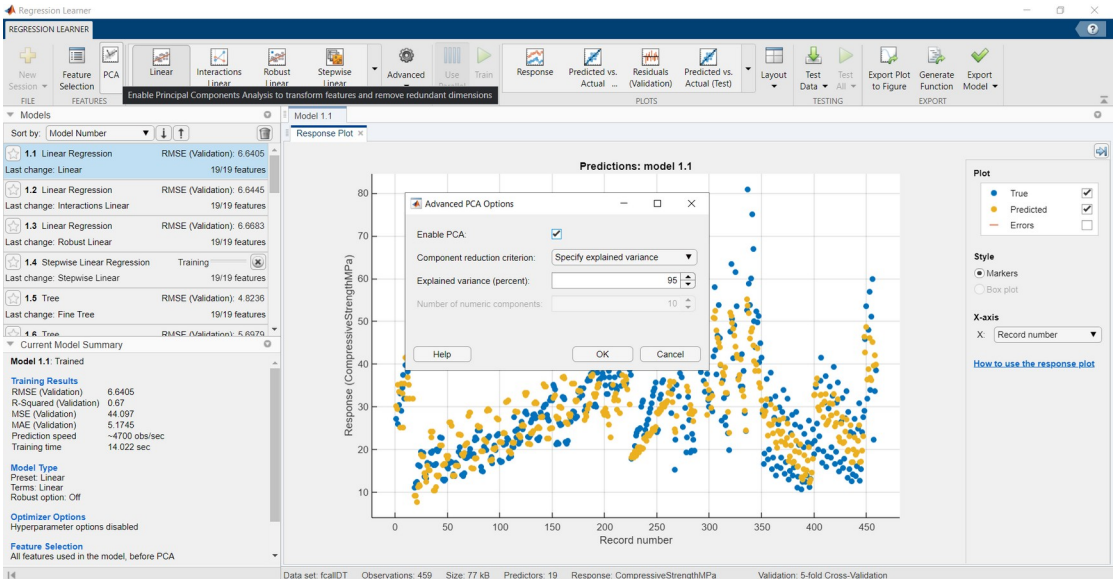



Figure 5.8.63 Figure to show the activation of PCA functionality

The PCA variables could be seen by first exporting the model. Now that the model is in the workspace, type the name of the model dot PCACoefficents. The Coefficients would be written in such a way such that the first row would contain the first feature and so on and so forth. The columns would denote each different primary component (PC). The first column would contain PC1 and so on and so forth.

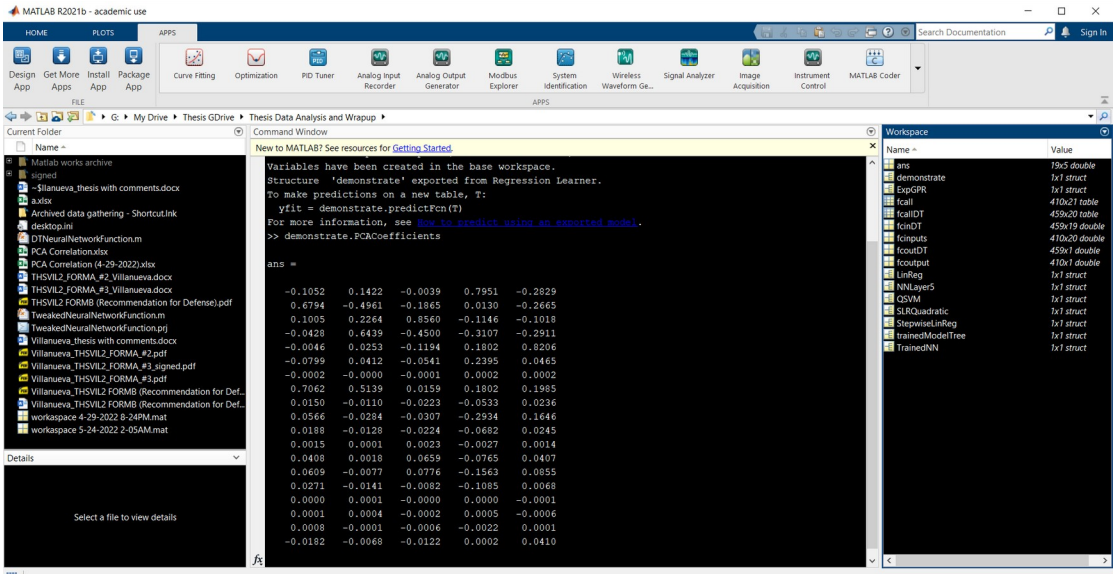



Figure 5.8.64 Figure to show the PCA coefficients

The analysis that was done was augmented using the Neural Network Fitting tool in MATLAB. One thing that is peculiar is that the MSE varies widely between each iteration. Except for when the hidden layer is either exceedingly small or excessively big (which in this case would be if the layer is two or less or six or more respectively), the values oscillate so widely and unpredictably that there is an impression that the modeling would have been both a trial-and-error process and an exercise in selection bias.

Using the PCA analysis alone would have excluded the age of concrete and the non-destructive tests to be part of the important factors, and thus, the linear regression result

has been included with regards to finding the important factors. An alternative approach would be to use the factors that PCA would find important and add the NDT tests and age of concrete. One more alternative approach would be to simply use the factors found by PCA to be important.

The NDT tweaked NN model with reduced factors was deemed to be the best model given that the factors have been reduced and out of the candidates, the MSE is acceptable and is better than the DT only counterpart.

# Chapter VI

## Conclusions and Recommendations

### VI.1 Conclusion

It was demonstrated that neural networks could give results better than other methods could. This could be demonstrated based on the R-squared value of the tweaked neural network. Nevertheless, the investigation also made known that more data would be appreciated, especially outside of the 10-45MPa range. This is since high strength concrete is used in some applications such as in skyscrapers. (*High-Strength Concrete*, n.d.) High strength concrete is used in those applications to minimize costs that would be needed if more columns are necessitated to carry the load. (*High Strength Concrete — What, why, & How? – Nevada Ready Mix*, n.d.)

The non-negligible loss that would be created by using PCA could also be a sign that more data would be desired for the factors that were less commonly encountered. This is important since there are few data that uses these factors when compared to data that uses the traditional factors such as cement, fine aggregate and coarse aggregate added and

water to binder ratio.

With consideration to the model that would be chosen, the important values as determined through data with NDT would be used. The important parameters for NDT are as follows: cement, fine aggregates, coarse aggregates, coarse RCA, fine RCA, water content, total unit weight, granite fines, fly ash content, ground granulated blast furnace slag, filler, crumb rubber, metakaolin content, content superplasticizer %, rebound number, and UPV.

The research was able to compare results from destructive methods with non-destructive methods. It was found that it is possible to create a dependable model even if the non-destructive methods were excluded. This is due to correlations such as the rebound number proportionally increasing with the age of the concrete.

Models using the factors to be considered have been created. Models using linear regression, stepwise quadratic regression with interactions, untweaked neural network and tweaked neural network have been created.

A model for the compressive strength of concrete from non-destructive test using machine learning has been

obtained. The model is a neural network that contains only the more influential variables. This model could be seen on subsection V.5.3.2 (page 166). This model (tweak neural network) is the best due to the higher R-squared compared to the other models. The best model contains twenty-one inputs with a hidden layer of size one to produce one output. This model has an R-squared of 0.9773.

## VI.2 Recommendations

More data is recommended to be gathered. The analysis could be augmented if there is more data. An acquisition of more date would be appreciated to cover better the factors, other than the commonly understood factors (cement, coarse and fine natural aggregates, course and fine recycled aggregates, water content, total unit weight, and fly ash content).

It should be noted that the model would have an ideal amount of sample if $20p<m$, where $p$ is the number of predictors and $m$ is the limiting sample size. Given that the compressive strength is a continuous function, $m$ would be equal to the sample size used. For the work cited, it would be acceptable even if just $10p<m$ is satisfied for “average” values. This would state that we could concede with only

satisfying the equation $10p<m$, but the criteria of $20p<m$ would ideally be satisfied too (Harrell , 2015).

Better methods to include missing data, especially those missing NDT test results not included in the study should be analyzed. Missing out entire results that include NDT factors not considered should be mitigated if possible since we might be locked out of various combinations such as how Leeb hardness correlates with UPV. Treating the NDT test results as zero for the missing data would simply introduce undue inaccuracies since unlike the less important additions to concrete (such as nano silica content), it would be wrong to say that the missing NDT variables would be zero. Stating that variables zero would be wrong since it would create a discontinuity; the behavior of the variable would not be as expected when taking into consideration the values needed to bring about a non-zero result from the other observations.

It would help if more of the factors are existent on both datasets. There are seven factors (excluding NDT factors) that are zeroed out in the dataset that contains only destructive testing factors. More data would allow a better splitting of data without compromising too much the other dataset. This better splitting would allow a better analysis with regards to

the factors and thus, more of the factors could be included. The splitting was not made to have more of the factors since it would have violated the minimum amount of data points in the model. (Harrell, 2015)

The only non-destructive factor that was used in the analysis are rebound number and ultrasonic pulse velocity. Other factors should be added to the analysis to have a better view of the situation.

Point load test could also be used to find the compressive strength of a concrete. Point load test is a cheaper way to test the compressive strength of concrete. However, its results would need to be correlated with destructive compressive strength tests to get the result and the test is only destructive and not non-destructive. (Kazemi et al., 2020) (Franklin, 1985)

Other factors such as Leeb hardness could be used but would still need a greater foray into the current research to get the data needed. Leeb Hardness could be used as an alternative to Schmidt Rebound Number, considering that Leeb Hardness was able to demonstrate better results. Schmidt rebound hammer provides an information on

material hardness from deeper surface layer, while Leeb rebound number seems to be informative of very thin surface layer of concrete. (Kovler et al., 2018).

Electrical resistivity might be usable with regards to determining the compressive strength. However, there would need to be more experiments testing the correlation between compressive strength and electrical resistivity. Electrical resistivity is currently used to test the resistance of concrete to corrosion. (Singh & Singh, 2018)

The electrical resistivity test used is the Wenner Array Four Probe method. The fact that Four copper probes/strips of size $10\,mm \times 50\,mm \times 2\,mm$ were embedded in the cubes at the time of casting to find the electrical resistivity means that it still needs further exploration as to how to make the concrete rebars be a sufficient alternative to the copper strips used when it comes to measuring the electrical resistivity, lest the method would not be practical for use in the field from the undue added cost that would be need to use electrical resistivity if using four copper strips would still need to be applied to the elements. (Singh & Singh, 2018) Given the scale of civil engineering projects, even the small additions of thin strips would add up to a big cost.

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# APPENDIX A

## Raw Data Legends

The Legend for raw data of NDT would be as follows:

Table 0-47 Legend of the raw data. The symbol on the left corresponds to the factor on the right.

| Symbol | Factor |
|---|---|
| A | Cement (kg/m^3) |
| B | Coarse aggregates (kg/m^3) |
| C | Fine aggregates (kg/m^3) |
| D | Coarse RCA (kg/m^3) |
| E | Fine RCA (kg/m^3) |
| F | Water content (kg/m^3) |
| G | Water to binder ratio |
| H | Total Unit Weight (kg/m^3) |
| I | Granite Fines (kg/m^3) |
| J | Fly ash content (kg/m^3) |
| K | Ground Granulated Blast Furnace Slag (GGBS) (kg/m^3) |
| L | Nano Silica (kg/m^3) |
| M | Filler (kg/m^3) |
| N | Crumb Rubber (kg/m^3) |
| O | Metakaolinite Content (kg/m^3) |
| P | polypropylene fibre (% by volume) |
| Q | dry curing |
| R | Superplasticizer (%) |
| S | (Schmidt) Rebound number |
| T | UPV (km/s) |
| U | Age of concrete (days) |
| V | Compressive strength (MPa) |

The symbol on the left corresponds to the factor on the right in the raw data tables. A correspond to Cement (kg/m^3), B corresponds to Coarse aggregates

(kg/m^3) and so on and so forth. It has been done this way since the factor would not fit.

## APPENDIX B

## Raw Data

Table 0-48 NDT raw data

| A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R | S | T | U | V |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1200 | 650 | 0 | 0 | 48 | 0.12 | 2298 | 0 | 0 | 0 | 0 | 0 | 0 | 400 | 0 | 0 | 3.5 | 27.10 | 3.25 | 28 | 27.3 |
| 0 | 1200 | 650 | 0 | 0 | 60 | 0.12 | 2410 | 0 | 0 | 0 | 0 | 0 | 0 | 500 | 0 | 0 | 3.5 | 30.2 | 3.37 | 28 | 29.5 |
| 0 | 1200 | 650 | 0 | 0 | 42 | 0.12 | 2242 | 0 | 0 | 0 | 0 | 0 | 0 | 350 | 0 | 0 | 3.5 | 25.6 | 3.19 | 28 | 25.9 |
| 0 | 1200 | 650 | 0 | 0 | 48 | 0.12 | 2298 | 0 | 0 | 0 | 0 | 0 | 0 | 400 | 0 | 0 | 3.5 | 30.8 | 3.41 | 28 | 30.4 |
| 0 | 1200 | 650 | 0 | 0 | 60 | 0.12 | 2410 | 0 | 0 | 0 | 0 | 0 | 0 | 500 | 0 | 0 | 3.5 | 31.9 | 3.53 | 28 | 33.2 |
| 0 | 1200 | 650 | 0 | 0 | 42 | 0.12 | 2242 | 0 | 0 | 0 | 0 | 0 | 0 | 350 | 0 | 0 | 3.5 | 28.1 | 3.3 | 28 | 29.1 |
| 0 | 1200 | 650 | 0 | 0 | 48 | 0.12 | 2298 | 0 | 0 | 0 | 0 | 0 | 0 | 400 | 0 | 0 | 3.5 | 33.7 | 3.58 | 28 | 34.5 |
| 0 | 1200 | 650 | 0 | 0 | 60 | 0.12 | 2410 | 0 | 0 | 0 | 0 | 0 | 0 | 500 | 0 | 0 | 3.5 | 35.8 | 3.69 | 28 | 37.4 |
| 0 | 1200 | 650 | 0 | 0 | 42 | 0.12 | 2242 | 0 | 0 | 0 | 0 | 0 | 0 | 350 | 0 | 0 | 3.5 | 31.5 | 3.49 | 28 | 32 |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1200 | 650 | 0 | 0 | 40 | 0.1 | 2290 | 0 | 400 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 29.5 | 3.81 | 28 | 39.8 |
| 0 | 1200 | 650 | 0 | 0 | 50 | 0.1 | 2400 | 0 | 500 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 32.2 | 3.89 | 28 | 41.7 |
| 0 | 1200 | 650 | 0 | 0 | 35 | 0.1 | 2235 | 0 | 350 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 28.2 | 3.7 | 28 | 38.3 |
| 0 | 1200 | 650 | 0 | 0 | 40 | 0.1 | 2290 | 0 | 400 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 33.2 | 3.92 | 28 | 42.9 |
| 0 | 1200 | 650 | 0 | 0 | 50 | 0.1 | 2400 | 0 | 500 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 35.6 | 3.99 | 28 | 45.5 |
| 0 | 1200 | 650 | 0 | 0 | 35 | 0.1 | 2235 | 0 | 350 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 30.6 | 3.83 | 28 | 40.5 |
| 0 | 1200 | 650 | 0 | 0 | 40 | 0.1 | 2290 | 0 | 400 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 36.2 | 4.03 | 28 | 45.9 |
| 0 | 1200 | 650 | 0 | 0 | 50 | 0.1 | 2400 | 0 | 500 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 38.5 | 4.11 | 28 | 49.3 |
| 0 | 1200 | 650 | 0 | 0 | 35 | 0.1 | 2235 | 0 | 350 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.5 | 33.9 | 3.93 | 28 | 43.1 |
| 273 | 0 | 936 | 0 | 0 | 216 | 0.79 | 1425 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14 | 3.55 | 7 | 11.1 |
| 273 | 0 | 936 | 0 | 0 | 216 | 0.79 | 1425 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 3.39 | 7 | 12.2 |
| 273 | 0 | 936 | 0 | 0 | 216 | 0.79 | 1425 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 17 | 3.49 | 7 | 12.4 |
| 273 | 0 | 936 | 0 | 0 | 216 | 0.79 | 1425 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 4.05 | 28 | 16.4 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 273 | 0 | 936 | 0 | 0 | 216 | 0.79 | 1425 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19 | 4.03 | 28 | 16.2 |
| 273 | 0 | 936 | 0 | 0 | 216 | 0.79 | 1425 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 4.02 | 28 | 16 |
| 273 | 0 | 936 | 0 | 0 | 216 | 0.79 | 1425 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 4.23 | 90 | 19.5 |
| 273 | 0 | 936 | 0 | 0 | 216 | 0.79 | 1425 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 4.23 | 90 | 18.7 |
| 273 | 0 | 936 | 0 | 0 | 216 | 0.79 | 1425 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 4.29 | 90 | 19.2 |
| 244 | 497 | 478 | 0 | 0 | 193 | 0.79 | 1412 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 15 | 3.55 | 7 | 13.7 |
| 244 | 497 | 478 | 0 | 0 | 193 | 0.79 | 1412 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14 | 3.58 | 7 | 14.1 |
| 244 | 497 | 478 | 0 | 0 | 193 | 0.79 | 1412 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14 | 3.37 | 7 | 13.3 |
| 244 | 497 | 478 | 0 | 0 | 193 | 0.79 | 1412 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 4.1 | 28 | 16.9 |
| 244 | 497 | 478 | 0 | 0 | 193 | 0.79 | 1412 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19 | 4.11 | 28 | 16.7 |
| 244 | 497 | 478 | 0 | 0 | 193 | 0.79 | 1412 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 4.16 | 28 | 16.7 |
| 244 | 497 | 478 | 0 | 0 | 193 | 0.79 | 1412 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 4.41 | 90 | 19.3 |
| 244 | 497 | 478 | 0 | 0 | 193 | 0.79 | 1412 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 4.39 | 90 | 19.3 |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 244 | 497 | 478 | 0 | 0 | 193 | 0.79 | 1412 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 4.39 | 90 | 19.7 |
| 291 | 0 | 927 | 0 | 0 | 215 | 0.74 | 1433 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 3.7 | 7 | 16.3 |
| 291 | 0 | 927 | 0 | 0 | 215 | 0.74 | 1433 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 3.87 | 7 | 16.4 |
| 291 | 0 | 927 | 0 | 0 | 215 | 0.74 | 1433 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19 | 3.71 | 7 | 16.7 |
| 291 | 0 | 927 | 0 | 0 | 215 | 0.74 | 1433 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 4.17 | 28 | 20 |
| 291 | 0 | 927 | 0 | 0 | 215 | 0.74 | 1433 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 4.19 | 28 | 19.6 |
| 291 | 0 | 927 | 0 | 0 | 215 | 0.74 | 1433 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 4.18 | 28 | 20.1 |
| 291 | 0 | 927 | 0 | 0 | 215 | 0.74 | 1433 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 4.35 | 90 | 22.8 |
| 291 | 0 | 927 | 0 | 0 | 215 | 0.74 | 1433 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 4.43 | 90 | 20.9 |
| 291 | 0 | 927 | 0 | 0 | 215 | 0.74 | 1433 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 4.37 | 90 | 22.7 |
| 261 | 493 | 473 | 0 | 0 | 193 | 0.74 | 1420 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 3.76 | 7 | 13 |
| 261 | 493 | 473 | 0 | 0 | 193 | 0.74 | 1420 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 3.73 | 7 | 12.8 |
| 261 | 493 | 473 | 0 | 0 | 193 | 0.74 | 1420 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 3.77 | 7 | 13 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 261 | 493 | 473 | 0 | 0 | 193 | 0.74 | 1420 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 4.12 | 28 | 16 |
| 261 | 493 | 473 | 0 | 0 | 193 | 0.74 | 1420 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 4.12 | 28 | 16.6 |
| 261 | 493 | 473 | 0 | 0 | 193 | 0.74 | 1420 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 4.13 | 28 | 15.6 |
| 261 | 493 | 473 | 0 | 0 | 193 | 0.74 | 1420 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 4.35 | 90 | 16.8 |
| 261 | 493 | 473 | 0 | 0 | 193 | 0.74 | 1420 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 4.39 | 90 | 17.2 |
| 261 | 493 | 473 | 0 | 0 | 193 | 0.74 | 1420 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 4.35 | 90 | 17 |
| 313 | 0 | 915 | 0 | 0 | 216 | 0.69 | 1444 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19 | 3.79 | 7 | 13.9 |
| 313 | 0 | 915 | 0 | 0 | 216 | 0.69 | 1444 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 3.75 | 7 | 14.2 |
| 313 | 0 | 915 | 0 | 0 | 216 | 0.69 | 1444 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19 | 3.68 | 7 | 13.8 |
| 313 | 0 | 915 | 0 | 0 | 216 | 0.69 | 1444 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 15 | 3.96 | 28 | 17 |
| 313 | 0 | 915 | 0 | 0 | 216 | 0.69 | 1444 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 15 | 3.93 | 28 | 16.7 |
| 313 | 0 | 915 | 0 | 0 | 216 | 0.69 | 1444 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14 | 3.95 | 28 | 16 |
| 313 | 0 | 915 | 0 | 0 | 216 | 0.69 | 1444 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19 | 4.23 | 90 | 19.4 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 313 | 0 | 915 | 0 | 0 | 216 | 0.69 | 1444 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 4.23 | 90 | 20.5 |
| 313 | 0 | 915 | 0 | 0 | 216 | 0.69 | 1444 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 4.22 | 90 | 18.7 |
| 280 | 487 | 469 | 0 | 0 | 193 | 0.69 | 1429 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19 | 3.88 | 7 | 14.1 |
| 280 | 487 | 469 | 0 | 0 | 193 | 0.69 | 1429 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 3.86 | 7 | 13.8 |
| 280 | 487 | 469 | 0 | 0 | 193 | 0.69 | 1429 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 3.87 | 7 | 14.5 |
| 280 | 487 | 469 | 0 | 0 | 193 | 0.69 | 1429 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 15 | 4.08 | 28 | 18.1 |
| 280 | 487 | 469 | 0 | 0 | 193 | 0.69 | 1429 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 16 | 4.09 | 28 | 18 |
| 280 | 487 | 469 | 0 | 0 | 193 | 0.69 | 1429 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 16 | 4.02 | 28 | 18.2 |
| 280 | 487 | 469 | 0 | 0 | 193 | 0.69 | 1429 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 4.45 | 90 | 18.5 |
| 280 | 487 | 469 | 0 | 0 | 193 | 0.69 | 1429 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 4.34 | 90 | 19.4 |
| 280 | 487 | 469 | 0 | 0 | 193 | 0.69 | 1429 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 4.39 | 90 | 20.1 |
| 332 | 0 | 920 | 0 | 0 | 216 | 0.65 | 1468 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 3.93 | 7 | 18.5 |
| 332 | 0 | 920 | 0 | 0 | 216 | 0.65 | 1468 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 3.95 | 7 | 18.5 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 332 | 0 | 920 | 0 | 0 | 216 | 0.65 | 1468 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 3.94 | 7 | 19 |
| 332 | 0 | 920 | 0 | 0 | 216 | 0.65 | 1468 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 4.09 | 28 | 22.1 |
| 332 | 0 | 920 | 0 | 0 | 216 | 0.65 | 1468 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 4.09 | 28 | 22.9 |
| 332 | 0 | 920 | 0 | 0 | 216 | 0.65 | 1468 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 4.11 | 28 | 22.5 |
| 332 | 0 | 920 | 0 | 0 | 216 | 0.65 | 1468 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 4.45 | 90 | 24.5 |
| 332 | 0 | 920 | 0 | 0 | 216 | 0.65 | 1468 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.48 | 90 | 24.8 |
| 332 | 0 | 920 | 0 | 0 | 216 | 0.65 | 1468 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 4.5 | 90 | 24.5 |
| 297 | 529 | 509 | 0 | 0 | 193 | 0.65 | 1528 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19 | 3.84 | 7 | 16 |
| 297 | 529 | 509 | 0 | 0 | 193 | 0.65 | 1528 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19 | 3.92 | 7 | 15 |
| 297 | 529 | 509 | 0 | 0 | 193 | 0.65 | 1528 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19 | 3.91 | 7 | 14.9 |
| 297 | 529 | 509 | 0 | 0 | 193 | 0.65 | 1528 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 4.16 | 28 | 20.7 |
| 297 | 529 | 509 | 0 | 0 | 193 | 0.65 | 1528 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 4.14 | 28 | 20.1 |
| 297 | 529 | 509 | 0 | 0 | 193 | 0.65 | 1528 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 4.14 | 28 | 19.8 |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 297 | 529 | 509 | 0 | 0 | 193 | 0.65 | 1528 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 4.42 | 90 | 22.5 |
| 297 | 529 | 509 | 0 | 0 | 193 | 0.65 | 1528 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 4.34 | 90 | 22.7 |
| 297 | 529 | 509 | 0 | 0 | 193 | 0.65 | 1528 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 4.41 | 90 | 23.1 |
| 354 | 0 | 909 | 0 | 0 | 216 | 0.61 | 1479 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 3.93 | 7 | 17.6 |
| 354 | 0 | 909 | 0 | 0 | 216 | 0.61 | 1479 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 3.93 | 7 | 18.2 |
| 354 | 0 | 909 | 0 | 0 | 216 | 0.61 | 1479 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19 | 3.93 | 7 | 16.8 |
| 354 | 0 | 909 | 0 | 0 | 216 | 0.61 | 1479 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 4.09 | 28 | 20.2 |
| 354 | 0 | 909 | 0 | 0 | 216 | 0.61 | 1479 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 4.18 | 28 | 21 |
| 354 | 0 | 909 | 0 | 0 | 216 | 0.61 | 1479 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 4.09 | 28 | 19.8 |
| 354 | 0 | 909 | 0 | 0 | 216 | 0.61 | 1479 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 4.35 | 90 | 23.2 |
| 354 | 0 | 909 | 0 | 0 | 216 | 0.61 | 1479 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 4.51 | 90 | 23.5 |
| 354 | 0 | 909 | 0 | 0 | 216 | 0.61 | 1479 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 4.37 | 90 | 23.7 |
| 316 | 524 | 504 | 0 | 0 | 193 | 0.61 | 1537 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 4.02 | 7 | 17.4 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 316 | 524 | 504 | 0 | 0 | 193 | 0.61 | 1537 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 4.01 | 7 | 17 |
| 316 | 524 | 504 | 0 | 0 | 193 | 0.61 | 1537 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 4.03 | 7 | 17.2 |
| 316 | 524 | 504 | 0 | 0 | 193 | 0.61 | 1537 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 4.12 | 28 | 21.3 |
| 316 | 524 | 504 | 0 | 0 | 193 | 0.61 | 1537 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 4.25 | 28 | 21.1 |
| 316 | 524 | 504 | 0 | 0 | 193 | 0.61 | 1537 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 4.1 | 28 | 21.5 |
| 316 | 524 | 504 | 0 | 0 | 193 | 0.61 | 1537 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 4.44 | 90 | 21.4 |
| 316 | 524 | 504 | 0 | 0 | 193 | 0.61 | 1537 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.62 | 90 | 22.7 |
| 316 | 524 | 504 | 0 | 0 | 193 | 0.61 | 1537 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 27 | 4.52 | 90 | 22.3 |
| 372 | 0 | 905 | 0 | 0 | 216 | 0.58 | 1493 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19 | 3.9 | 7 | 18.1 |
| 372 | 0 | 905 | 0 | 0 | 216 | 0.58 | 1493 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19 | 3.96 | 7 | 18.4 |
| 372 | 0 | 905 | 0 | 0 | 216 | 0.58 | 1493 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 4 | 7 | 18.4 |
| 372 | 0 | 905 | 0 | 0 | 216 | 0.58 | 1493 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 4.13 | 28 | 20.8 |
| 372 | 0 | 905 | 0 | 0 | 216 | 0.58 | 1493 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 4.1 | 28 | 20.5 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 372 | 0 | 905 | 0 | 0 | 216 | 0.58 | 1493 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 4.43 | 28 | 27.6 |
| 372 | 0 | 905 | 0 | 0 | 216 | 0.58 | 1493 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 4.43 | 90 | 24.3 |
| 372 | 0 | 905 | 0 | 0 | 216 | 0.58 | 1493 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 4.47 | 90 | 22.9 |
| 372 | 0 | 905 | 0 | 0 | 216 | 0.58 | 1493 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 4.39 | 90 | 24.7 |
| 332 | 530 | 490 | 0 | 0 | 193 | 0.58 | 1545 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 4.17 | 7 | 21.3 |
| 332 | 530 | 490 | 0 | 0 | 193 | 0.58 | 1545 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.23 | 7 | 22.1 |
| 332 | 530 | 490 | 0 | 0 | 193 | 0.58 | 1545 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.29 | 7 | 22.1 |
| 332 | 530 | 490 | 0 | 0 | 193 | 0.58 | 1545 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 26 | 4.39 | 28 | 26.6 |
| 332 | 530 | 490 | 0 | 0 | 193 | 0.58 | 1545 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 27 | 4.41 | 28 | 24.7 |
| 332 | 530 | 490 | 0 | 0 | 193 | 0.58 | 1545 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 27 | 4.42 | 28 | 25.5 |
| 332 | 530 | 490 | 0 | 0 | 193 | 0.58 | 1545 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.62 | 90 | 28.7 |
| 332 | 530 | 490 | 0 | 0 | 193 | 0.58 | 1545 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.62 | 90 | 28.9 |
| 332 | 530 | 490 | 0 | 0 | 193 | 0.58 | 1545 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.62 | 90 | 28.3 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 400 | 0 | 890 | 0 | 0 | 216 | 0.54 | 1506 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 4.09 | 7 | 23 |
| 400 | 0 | 890 | 0 | 0 | 216 | 0.54 | 1506 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 4.13 | 7 | 22.9 |
| 400 | 0 | 890 | 0 | 0 | 216 | 0.54 | 1506 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 4.12 | 7 | 23.2 |
| 400 | 0 | 890 | 0 | 0 | 216 | 0.54 | 1506 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.26 | 28 | 26.4 |
| 400 | 0 | 890 | 0 | 0 | 216 | 0.54 | 1506 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 27 | 4.25 | 28 | 27.1 |
| 400 | 0 | 890 | 0 | 0 | 216 | 0.54 | 1506 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 4.24 | 28 | 28.1 |
| 400 | 0 | 890 | 0 | 0 | 216 | 0.54 | 1506 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 27 | 4.54 | 90 | 28.3 |
| 400 | 0 | 890 | 0 | 0 | 216 | 0.54 | 1506 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 27 | 4.48 | 90 | 27.4 |
| 400 | 0 | 890 | 0 | 0 | 216 | 0.54 | 1506 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 27 | 4.51 | 90 | 27.6 |
| 357 | 528 | 488 | 0 | 0 | 193 | 0.54 | 1566 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 4.23 | 7 | 22.5 |
| 357 | 528 | 488 | 0 | 0 | 193 | 0.54 | 1566 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 4.2 | 7 | 22.2 |
| 357 | 528 | 488 | 0 | 0 | 193 | 0.54 | 1566 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 4.23 | 7 | 22.9 |
| 357 | 528 | 488 | 0 | 0 | 193 | 0.54 | 1566 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.39 | 28 | 28.6 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 357 | 528 | 488 | 0 | 0 | 193 | 0.54 | 1566 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 4.4 | 28 | 28 |
| 357 | 528 | 488 | 0 | 0 | 193 | 0.54 | 1566 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 4.43 | 28 | 27.6 |
| 357 | 528 | 488 | 0 | 0 | 193 | 0.54 | 1566 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 4.53 | 90 | 29.9 |
| 357 | 528 | 488 | 0 | 0 | 193 | 0.54 | 1566 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 4.51 | 90 | 30.5 |
| 357 | 528 | 488 | 0 | 0 | 193 | 0.54 | 1566 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 26 | 4.55 | 90 | 30.6 |
| 432 | 0 | 935 | 0 | 0 | 216 | 0.5 | 1583 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 4.21 | 7 | 28.1 |
| 432 | 0 | 935 | 0 | 0 | 216 | 0.5 | 1583 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 26 | 4.18 | 7 | 27.4 |
| 432 | 0 | 935 | 0 | 0 | 216 | 0.5 | 1583 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 26 | 4.23 | 7 | 26.8 |
| 432 | 0 | 935 | 0 | 0 | 216 | 0.5 | 1583 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 4.28 | 28 | 31.6 |
| 432 | 0 | 935 | 0 | 0 | 216 | 0.5 | 1583 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 27 | 4.32 | 28 | 32.2 |
| 432 | 0 | 935 | 0 | 0 | 216 | 0.5 | 1583 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 26 | 4.28 | 28 | 31.5 |
| 432 | 0 | 935 | 0 | 0 | 216 | 0.5 | 1583 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32 | 4.65 | 90 | 35.1 |
| 432 | 0 | 935 | 0 | 0 | 216 | 0.5 | 1583 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32 | 4.62 | 90 | 34.8 |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 432 | 0 | 935 | 0 | 0 | 216 | 0.5 | 1583 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32 | 4.61 | 90 | 34.1 |
| 386 | 550 | 469 | 0 | 0 | 193 | 0.5 | 1598 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 4.17 | 7 | 21.3 |
| 386 | 550 | 469 | 0 | 0 | 193 | 0.5 | 1598 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 4.18 | 7 | 21.7 |
| 386 | 550 | 469 | 0 | 0 | 193 | 0.5 | 1598 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 4.12 | 7 | 21.3 |
| 386 | 550 | 469 | 0 | 0 | 193 | 0.5 | 1598 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 4.31 | 28 | 26.2 |
| 386 | 550 | 469 | 0 | 0 | 193 | 0.5 | 1598 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 4.32 | 28 | 25.8 |
| 386 | 550 | 469 | 0 | 0 | 193 | 0.5 | 1598 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 4.32 | 28 | 25.8 |
| 386 | 550 | 469 | 0 | 0 | 193 | 0.5 | 1598 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 4.66 | 90 | 32.4 |
| 386 | 550 | 469 | 0 | 0 | 193 | 0.5 | 1598 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 27 | 4.66 | 90 | 32.2 |
| 386 | 550 | 469 | 0 | 0 | 193 | 0.5 | 1598 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 29 | 4.7 | 90 | 31.7 |
| 480 | 0 | 908 | 0 | 0 | 216 | 0.45 | 1604 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 4.02 | 7 | 21.8 |
| 480 | 0 | 908 | 0 | 0 | 216 | 0.45 | 1604 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.08 | 7 | 21.3 |
| 480 | 0 | 908 | 0 | 0 | 216 | 0.45 | 1604 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 4.07 | 7 | 22 |

| | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 480 | 0 | 908 | 0 | 0 | 216 | 0.45 | 1604 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.24 | 28 | 28.3 |
| 480 | 0 | 908 | 0 | 0 | 216 | 0.45 | 1604 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.23 | 28 | 27.6 |
| 480 | 0 | 908 | 0 | 0 | 216 | 0.45 | 1604 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 4.17 | 28 | 26.5 |
| 480 | 0 | 908 | 0 | 0 | 216 | 0.45 | 1604 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.65 | 90 | 28.4 |
| 480 | 0 | 908 | 0 | 0 | 216 | 0.45 | 1604 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 4.59 | 90 | 29 |
| 480 | 0 | 908 | 0 | 0 | 216 | 0.45 | 1604 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 27 | 4.67 | 90 | 28.9 |
| 429 | 533 | 412 | 0 | 0 | 193 | 0.45 | 1567 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.25 | 7 | 27.3 |
| 429 | 533 | 412 | 0 | 0 | 193 | 0.45 | 1567 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 26 | 4.19 | 7 | 27.4 |
| 429 | 533 | 412 | 0 | 0 | 193 | 0.45 | 1567 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.08 | 7 | 27.8 |
| 429 | 533 | 412 | 0 | 0 | 193 | 0.45 | 1567 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 4.45 | 28 | 33.6 |
| 429 | 533 | 412 | 0 | 0 | 193 | 0.45 | 1567 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 4.37 | 28 | 32.1 |
| 429 | 533 | 412 | 0 | 0 | 193 | 0.45 | 1567 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 4.45 | 28 | 34.4 |
| 429 | 533 | 412 | 0 | 0 | 193 | 0.45 | 1567 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 34 | 4.78 | 90 | 34.1 |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 429 | 533 | 412 | 0 | 0 | 193 | 0.45 | 1567 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32 | 4.73 | 90 | 32.7 |
| 429 | 533 | 412 | 0 | 0 | 193 | 0.45 | 1567 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 35 | 4.66 | 90 | 34.4 |
| 514 | 0 | 884 | 0 | 0 | 216 | 0.42 | 1614 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23 | 4.18 | 7 | 29.1 |
| 514 | 0 | 884 | 0 | 0 | 216 | 0.42 | 1614 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 24 | 4.17 | 7 | 30.2 |
| 514 | 0 | 884 | 0 | 0 | 216 | 0.42 | 1614 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.17 | 7 | 28.9 |
| 514 | 0 | 884 | 0 | 0 | 216 | 0.42 | 1614 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 29 | 4.38 | 28 | 36.1 |
| 514 | 0 | 884 | 0 | 0 | 216 | 0.42 | 1614 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 4.31 | 28 | 36.7 |
| 514 | 0 | 884 | 0 | 0 | 216 | 0.42 | 1614 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 29 | 4.31 | 28 | 36.2 |
| 514 | 0 | 884 | 0 | 0 | 216 | 0.42 | 1614 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 34 | 4.68 | 90 | 37.8 |
| 514 | 0 | 884 | 0 | 0 | 216 | 0.42 | 1614 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 35 | 4.69 | 90 | 37.2 |
| 514 | 0 | 884 | 0 | 0 | 216 | 0.42 | 1614 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 34 | 4.85 | 90 | 38 |
| 460 | 558 | 419 | 0 | 0 | 193 | 0.42 | 1630 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.36 | 7 | 30.2 |
| 460 | 558 | 419 | 0 | 0 | 193 | 0.42 | 1630 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.32 | 7 | 30.6 |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 460 | 558 | 419 | 0 | 0 | 193 | 0.42 | 1630 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 4.32 | 7 | 30.1 |
| 460 | 558 | 419 | 0 | 0 | 193 | 0.42 | 1630 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32 | 4.42 | 28 | 38 |
| 460 | 558 | 419 | 0 | 0 | 193 | 0.42 | 1630 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32 | 4.39 | 28 | 34.6 |
| 460 | 558 | 419 | 0 | 0 | 193 | 0.42 | 1630 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 31 | 4.52 | 28 | 36.3 |
| 460 | 558 | 419 | 0 | 0 | 193 | 0.42 | 1630 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 35 | 4.82 | 90 | 36.6 |
| 460 | 558 | 419 | 0 | 0 | 193 | 0.42 | 1630 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 36 | 4.9 | 90 | 36.8 |
| 460 | 558 | 419 | 0 | 0 | 193 | 0.42 | 1630 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 36 | 4.72 | 90 | 37.8 |
| 301 | 652 | 0 | 0 | 0 | 277 | 0.78 | 1286 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32.99 | 4.46 | 28 | 39.9 |
| 301 | 489 | 0 | 163 | 0 | 277 | 0.78 | 1286 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32 | 4.33 | 28 | 37 |
| 301 | 326 | 0 | 326 | 0 | 277 | 0.78 | 1286 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32 | 4.28 | 28 | 35 |
| 301 | 163 | 0 | 489 | 0 | 277 | 0.78 | 1286 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 29.98 | 4.18 | 28 | 33 |
| 301 | 0 | 0 | 652 | 0 | 277 | 0.78 | 1286 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30.02 | 4.16 | 28 | 33 |
| 301 | 652 | 410 | 0 | 410 | 277 | 0.78 | 2106 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32.99 | 4.33 | 28 | 38.5 |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 301 | 652 | 0 | 0 | 820 | 277 | 0.78 | 2106 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32 | 4.29 | 28 | 37 |
| 301 | 0 | 410 | 652 | 410 | 277 | 0.78 | 2106 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 29.98 | 4.1 | 28 | 35.2 |
| 301 | 0 | 0 | 652 | 820 | 277 | 0.78 | 2106 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 26.98 | 3.91 | 28 | 34.5 |
| 301 | 652 | 0 | 0 | 0 | 277 | 0.78 | 1286 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 34.02 | 4.61 | 56 | 42.5 |
| 301 | 489 | 0 | 163 | 0 | 277 | 0.78 | 1286 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32 | 4.48 | 56 | 40 |
| 301 | 326 | 0 | 326 | 0 | 277 | 0.78 | 1286 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32 | 4.36 | 56 | 37 |
| 301 | 163 | 0 | 489 | 0 | 277 | 0.78 | 1286 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 31.01 | 4.4 | 56 | 34.9 |
| 301 | 0 | 0 | 652 | 0 | 277 | 0.78 | 1286 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30.02 | 4.31 | 56 | 34 |
| 301 | 652 | 410 | 0 | 410 | 277 | 0.78 | 2106 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 34.02 | 4.48 | 56 | 40 |
| 301 | 652 | 0 | 0 | 820 | 277 | 0.78 | 2106 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32.99 | 4.37 | 56 | 38 |
| 301 | 0 | 410 | 652 | 410 | 277 | 0.78 | 2106 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32 | 4.26 | 56 | 37.5 |
| 301 | 0 | 0 | 652 | 820 | 277 | 0.78 | 2106 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 27.97 | 4.15 | 56 | 34.9 |
| 301 | 652 | 0 | 0 | 0 | 277 | 0.78 | 1286 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 34.02 | 4.62 | 90 | 43.5 |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 301 | 489 | 0 | 163 | 0 | 277 | 0.78 | 1286 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32.99 | 4.52 | 90 | 41.9 |
| 301 | 326 | 0 | 326 | 0 | 277 | 0.78 | 1286 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32.99 | 4.4 | 90 | 40 |
| 301 | 163 | 0 | 489 | 0 | 277 | 0.78 | 1286 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32 | 4.34 | 90 | 35.3 |
| 301 | 0 | 0 | 652 | 0 | 277 | 0.78 | 1286 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30.02 | 4.32 | 90 | 35.6 |
| 301 | 652 | 410 | 0 | 410 | 277 | 0.78 | 2106 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 34.02 | 4.48 | 90 | 42.8 |
| 301 | 652 | 0 | 0 | 820 | 277 | 0.78 | 2106 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 34.02 | 4.4 | 90 | 41 |
| 301 | 0 | 410 | 652 | 410 | 277 | 0.78 | 2106 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32 | 4.32 | 90 | 38.8 |
| 301 | 0 | 0 | 652 | 820 | 277 | 0.78 | 2106 | 0 | 55.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 29.02 | 4.21 | 90 | 37.5 |
| 269 | 832 | 1148 | 0 | 0 | 98.2 | 0.37 | 2373 | 0 | 0 | 0 | 0 | 104 | 0 | 0 | 0 | 0 | 0 | 40.7 | 5.1 | 28 | 52.3 |
| 135 | 833 | 1150 | 0 | 0 | 96.9 | 0.41 | 2351 | 0 | 103 | 0 | 0 | 104 | 0 | 0 | 0 | 0 | 0 | 30.48 | 4.89 | 28 | 47.3 |
| 135 | 833 | 1150 | 0 | 0 | 96.9 | 0.41 | 2375 | 0 | 103 | 0 | 2.4 | 104 | 0 | 0 | 0 | 0 | 0 | 38.74 | 5.01 | 28 | 58.9 |
| 135 | 833 | 1150 | 0 | 0 | 96.9 | 0.41 | 2347 | 0 | 103 | 0 | 4.7 | 104 | 0 | 0 | 0 | 0 | 0 | 45.43 | 5 | 28 | 49.7 |
| 135 | 833 | 1150 | 0 | 0 | 96.9 | 0.41 | 2358 | 0 | 103 | 0 | 7.1 | 104 | 0 | 0 | 0 | 0 | 0 | 32.65 | 4.66 | 28 | 43.9 |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 135 | 833 | 1035 | 0 | 0 | 96.9 | 0.41 | 2281 | 0 | 103 | 0 | 0 | 104 | 115 | 0 | 0 | 0 | 0 | 25.69 | 4.69 | 28 | 38.1 |
| 135 | 833 | 1035 | 0 | 0 | 96.9 | 0.41 | 2316 | 0 | 103 | 0 | 2.4 | 104 | 115 | 0 | 0 | 0 | 0 | 28.52 | 4.91 | 28 | 53.7 |
| 135 | 833 | 1035 | 0 | 0 | 96.9 | 0.41 | 2298 | 0 | 103 | 0 | 4.7 | 104 | 115 | 0 | 0 | 0 | 0 | 33.52 | 4.77 | 28 | 44.3 |
| 135 | 833 | 1035 | 0 | 0 | 96.9 | 0.41 | 2315 | 0 | 103 | 0 | 7.1 | 104 | 115 | 0 | 0 | 0 | 0 | 21.56 | 4.62 | 28 | 36.1 |
| 135 | 833 | 920 | 0 | 0 | 96.9 | 0.41 | 2226 | 0 | 103 | 0 | 0 | 104 | 230 | 0 | 0 | 0 | 0 | 19.6 | 4.4 | 28 | 33.5 |
| 135 | 833 | 920 | 0 | 0 | 96.9 | 0.41 | 2226 | 0 | 103 | 0 | 2.4 | 104 | 230 | 0 | 0 | 0 | 0 | 23.52 | 4.39 | 28 | 42.9 |
| 135 | 833 | 920 | 0 | 0 | 96.9 | 0.41 | 2190 | 0 | 103 | 0 | 4.7 | 104 | 230 | 0 | 0 | 0 | 0 | 27.65 | 4.44 | 28 | 37.7 |
| 135 | 833 | 920 | 0 | 0 | 96.9 | 0.41 | 2209 | 0 | 103 | 0 | 7.1 | 104 | 230 | 0 | 0 | 0 | 0 | 19.6 | 3.96 | 28 | 31.5 |
| 135 | 833 | 805 | 0 | 0 | 96.9 | 0.41 | 2171 | 0 | 103 | 0 | 0 | 104 | 345 | 0 | 0 | 0 | 0 | 15.69 | 3.25 | 28 | 30.1 |
| 135 | 833 | 805 | 0 | 0 | 96.9 | 0.41 | 2178 | 0 | 103 | 0 | 2.4 | 104 | 345 | 0 | 0 | 0 | 0 | 22.65 | 3.4 | 28 | 32.9 |
| 135 | 833 | 805 | 0 | 0 | 96.9 | 0.41 | 2171 | 0 | 103 | 0 | 4.7 | 104 | 345 | 0 | 0 | 0 | 0 | 18.52 | 3.24 | 28 | 33.1 |
| 135 | 833 | 805 | 0 | 0 | 96.9 | 0.41 | 2190 | 0 | 103 | 0 | 7.1 | 104 | 345 | 0 | 0 | 0 | 0 | 14.6 | 2.94 | 28 | 28.9 |
| 269 | 832 | 1148 | 0 | 0 | 98.2 | 0.37 | 2372 | 0 | 0 | 0 | 0 | 104 | 0 | 0 | 0 | 0 | 0 | 40.91 | 5.09 | 28 | 52.6 |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 269 | 832 | 1148 | 0 | 0 | 98.2 | 0.37 | 2398 | 0 | 0 | 0 | 2.69 | 104 | 0 | 0 | 0 | 0 | 0 | 51.96 | 5.24 | 28 | 80.9 |
| 269 | 832 | 1148 | 0 | 0 | 98.2 | 0.37 | 2389 | 0 | 0 | 0 | 5.37 | 104 | 0 | 0 | 0 | 0 | 0 | 44 | 5.05 | 28 | 58.9 |
| 269 | 832 | 1148 | 0 | 0 | 98.2 | 0.37 | 2359 | 0 | 0 | 0 | 8.06 | 104 | 0 | 0 | 0 | 0 | 0 | 35.92 | 5.01 | 28 | 53.9 |
| 269 | 832 | 1033 | 0 | 0 | 98.2 | 0.37 | 2313 | 0 | 0 | 0 | 0 | 104 | 115 | 0 | 0 | 0 | 0 | 44.95 | 5.15 | 28 | 60.1 |
| 269 | 832 | 1033 | 0 | 0 | 98.2 | 0.37 | 2326 | 0 | 0 | 0 | 2.69 | 104 | 115 | 0 | 0 | 0 | 0 | 48.99 | 5.18 | 28 | 75.1 |
| 269 | 832 | 1033 | 0 | 0 | 98.2 | 0.37 | 2317 | 0 | 0 | 0 | 5.37 | 104 | 115 | 0 | 0 | 0 | 0 | 46.97 | 5.02 | 28 | 67 |
| 269 | 832 | 1033 | 0 | 0 | 98.2 | 0.37 | 2308 | 0 | 0 | 0 | 8.06 | 104 | 115 | 0 | 0 | 0 | 0 | 32.95 | 4.76 | 28 | 50.1 |
| 269 | 832 | 918 | 0 | 0 | 98.2 | 0.37 | 2235 | 0 | 0 | 0 | 0 | 104 | 230 | 0 | 0 | 0 | 0 | 27.96 | 4.77 | 28 | 44 |
| 269 | 832 | 918 | 0 | 0 | 98.2 | 0.37 | 2259 | 0 | 0 | 0 | 2.69 | 104 | 230 | 0 | 0 | 0 | 0 | 37.94 | 4.92 | 28 | 52.4 |
| 269 | 832 | 918 | 0 | 0 | 98.2 | 0.37 | 2272 | 0 | 0 | 0 | 5.37 | 104 | 230 | 0 | 0 | 0 | 0 | 30.93 | 4.7 | 28 | 49.9 |
| 269 | 832 | 918 | 0 | 0 | 98.2 | 0.37 | 2263 | 0 | 0 | 0 | 8.06 | 104 | 230 | 0 | 0 | 0 | 0 | 25.94 | 4.74 | 28 | 51.3 |
| 269 | 832 | 804 | 0 | 0 | 98.2 | 0.37 | 2196 | 0 | 0 | 0 | 0 | 104 | 345 | 0 | 0 | 0 | 0 | 22.86 | 4.16 | 28 | 40.4 |
| 269 | 832 | 804 | 0 | 0 | 98.2 | 0.37 | 2199 | 0 | 0 | 0 | 2.69 | 104 | 345 | 0 | 0 | 0 | 0 | 26.9 | 4.31 | 28 | 45 |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 269 | 832 | 804 | 0 | 0 | 98.2 | 0.37 | 2184 | 0 | 0 | 0 | 5.37 | 104 | 345 | 0 | 0 | 0 | 0 | 19.89 | 3.81 | 28 | 41.6 |
| 269 | 832 | 804 | 0 | 0 | 98.2 | 0.37 | 2165 | 0 | 0 | 0 | 8.06 | 104 | 345 | 0 | 0 | 0 | 0 | 21.91 | 3.51 | 28 | 28.5 |
| 0 | 1290 | 549 | 0 | 0 | 92.5 | 0.23 | 2341 | 0 | 205 | 205 | 0 | 0 | 0 | 0 | 0 | 0 | 2.86 | 30.07 | 3.06 | 7 | 29.1 |
| 0 | 1290 | 549 | 0 | 0 | 92.5 | 0.23 | 2341 | 0 | 205 | 205 | 0 | 0 | 0 | 0 | 0 | 0 | 2.86 | 42.26 | 3.25 | 28 | 45.9 |
| 0 | 1290 | 549 | 0 | 0 | 92.5 | 0.23 | 2341 | 0 | 205 | 205 | 0 | 0 | 0 | 0 | 0 | 0 | 2.86 | 44.19 | 3.66 | 90 | 53.5 |
| 0 | 1290 | 439 | 0 | 0 | 92.5 | 0.23 | 2341 | 110 | 205 | 205 | 0 | 0 | 0 | 0 | 0 | 0 | 2.86 | 32.15 | 3.12 | 7 | 32 |
| 0 | 1290 | 439 | 0 | 0 | 92.5 | 0.23 | 2341 | 110 | 205 | 205 | 0 | 0 | 0 | 0 | 0 | 0 | 2.86 | 44.22 | 3.44 | 28 | 48.1 |
| 0 | 1290 | 439 | 0 | 0 | 92.5 | 0.23 | 2341 | 110 | 205 | 205 | 0 | 0 | 0 | 0 | 0 | 0 | 2.86 | 46.26 | 4.12 | 90 | 57 |
| 0 | 1290 | 329 | 0 | 0 | 92.5 | 0.23 | 2341 | 220 | 205 | 205 | 0 | 0 | 0 | 0 | 0 | 0 | 2.86 | 32.96 | 3.21 | 7 | 34 |
| 0 | 1290 | 329 | 0 | 0 | 92.5 | 0.23 | 2341 | 220 | 205 | 205 | 0 | 0 | 0 | 0 | 0 | 0 | 2.86 | 46.44 | 3.51 | 28 | 51.1 |
| 0 | 1290 | 329 | 0 | 0 | 92.5 | 0.23 | 2341 | 220 | 205 | 205 | 0 | 0 | 0 | 0 | 0 | 0 | 2.86 | 47.07 | 4.36 | 90 | 59.9 |
| 0 | 1290 | 220 | 0 | 0 | 92.5 | 0.23 | 2341 | 329 | 205 | 205 | 0 | 0 | 0 | 0 | 0 | 0 | 2.86 | 25.26 | 3.04 | 7 | 22.4 |
| 0 | 1290 | 220 | 0 | 0 | 92.5 | 0.23 | 2341 | 329 | 205 | 205 | 0 | 0 | 0 | 0 | 0 | 0 | 2.86 | 29.15 | 3.2 | 28 | 33.6 |

| | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1290 | 220 | 0 | 0 | 92.5 | 0.23 | 2341 | 329 | 205 | 205 | 0 | 0 | 0 | 0 | 0 | 0 | 2.86 | 31.74 | 3.45 | 90 | 38.6 |

Table 0-49 Destructive tests only raw data

| A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R | S | T | U | V |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 207 | 830 | 415 | 0 | 0 | 114 | 0.55 | 1565 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 17.9 |
| 207 | 830 | 415 | 0 | 0 | 114 | 0.55 | 1565 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 18.3 |
| 207 | 830 | 415 | 0 | 0 | 114 | 0.55 | 1565 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 18.5 |
| 207 | 830 | 415 | 0 | 0 | 114 | 0.55 | 1565 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14 | 20.9 |
| 207 | 830 | 415 | 0 | 0 | 114 | 0.55 | 1565 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14 | 23.3 |
| 207 | 830 | 415 | 0 | 0 | 114 | 0.55 | 1565 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14 | 23.9 |
| 207 | 830 | 415 | 0 | 0 | 114 | 0.55 | 1565 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 24.7 |
| 207 | 830 | 415 | 0 | 0 | 114 | 0.55 | 1565 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 24.8 |
| 207 | 830 | 415 | 0 | 0 | 114 | 0.55 | 1565 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 25.1 |
| 20 | 83 | 415 | 0 | 0 | 11 | 0.5 | 156 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 30. |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 7 | 0 | | | | 4 | 5 | 5 | | | | | | | | | | | | | | 1 |
| 207 | 830 | 415 | 0 | 0 | 114 | 0.55 | 1565 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 31.2 |
| 207 | 830 | 415 | 0 | 0 | 114 | 0.55 | 1565 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 31.6 |
| 264 | 790 | 395 | 0 | 0 | 132 | 0.5 | 1580 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 23.3 |
| 264 | 790 | 395 | 0 | 0 | 132 | 0.5 | 1580 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 24.7 |
| 264 | 790 | 395 | 0 | 0 | 132 | 0.5 | 1580 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 25.9 |
| 264 | 790 | 395 | 0 | 0 | 132 | 0.5 | 1580 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14 | 26.9 |
| 264 | 790 | 395 | 0 | 0 | 132 | 0.5 | 1580 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14 | 27.1 |
| 264 | 790 | 395 | 0 | 0 | 132 | 0.5 | 1580 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14 | 28.8 |
| 264 | 790 | 395 | 0 | 0 | 132 | 0.5 | 1580 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 29.7 |
| 264 | 790 | 395 | 0 | 0 | 132 | 0.5 | 1580 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 30.8 |
| 264 | 790 | 395 | 0 | 0 | 132 | 0.5 | 1580 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 32.6 |
| 264 | 790 | 395 | 0 | 0 | 132 | 0.5 | 1580 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 33.6 |
| 26 | 79 | 395 | 0 | 0 | 13 | 0.5 | 158 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 34. |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 0 | | | | 2 | | 0 | | | | | | | | | | | | | | 3 |
| 264 | 790 | 395 | 0 | 0 | 132 | 0.5 | 1580 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 35.7 |
| 363 | 725 | 363 | 0 | 0 | 163 | 0.45 | 1613 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 24 |
| 363 | 725 | 363 | 0 | 0 | 163 | 0.45 | 1613 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 24.6 |
| 363 | 725 | 363 | 0 | 0 | 163 | 0.45 | 1613 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 28.8 |
| 363 | 725 | 363 | 0 | 0 | 163 | 0.45 | 1613 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14 | 31.9 |
| 363 | 725 | 363 | 0 | 0 | 163 | 0.45 | 1613 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14 | 32.9 |
| 363 | 725 | 363 | 0 | 0 | 163 | 0.45 | 1613 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 35.8 |
| 363 | 725 | 363 | 0 | 0 | 163 | 0.45 | 1613 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 36.3 |
| 363 | 725 | 363 | 0 | 0 | 163 | 0.45 | 1613 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 39.7 |
| 363 | 725 | 363 | 0 | 0 | 163 | 0.45 | 1613 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 40.7 |
| 363 | 725 | 363 | 0 | 0 | 163 | 0.45 | 1613 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 42.1 |
| 363 | 725 | 363 | 0 | 0 | 163 | 0.45 | 1613 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 42.8 |
| 50 | 85 | 796 | 0 | 0 | 17 | 0.3 | 233 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1. | 0 | 0 | 3 | 44. |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 9 | 8 | | | | 6 | 3 | 9 | | | | | | | | | | 2 | | | | 6 |
| 509 | 858 | 796 | 0 | 0 | 176 | 0.33 | 2339 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.2 | 0 | 0 | 7 | 52.9 |
| 509 | 858 | 796 | 0 | 0 | 176 | 0.33 | 2339 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.2 | 0 | 0 | 28 | 57.5 |
| 475 | 858 | 769 | 0 | 0 | 197 | 0.4 | 2299 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.8 | 0 | 0 | 3 | 28.6 |
| 475 | 858 | 769 | 0 | 0 | 197 | 0.4 | 2299 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.8 | 0 | 0 | 7 | 34.1 |
| 475 | 858 | 769 | 0 | 0 | 197 | 0.4 | 2299 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.8 | 0 | 0 | 28 | 39.6 |
| 452 | 858 | 694 | 0 | 0 | 233 | 0.5 | 2237 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 15.3 |
| 452 | 858 | 694 | 0 | 0 | 233 | 0.5 | 2237 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 22.4 |
| 452 | 858 | 694 | 0 | 0 | 233 | 0.5 | 2237 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 35.2 |
| 269 | 832 | 1148 | 0 | 0 | 98.2 | 0.37 | 2373 | 0 | 0 | 0 | 0 | 104 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 47.3 |
| 135 | 833 | 1150 | 0 | 0 | 96.9 | 0.41 | 2351 | 0 | 103 | 0 | 0 | 104 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 32.5 |
| 135 | 833 | 1150 | 0 | 0 | 96.9 | 0.41 | 2375 | 0 | 103 | 0 | 2.4 | 104 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 37.9 |
| 135 | 833 | 1150 | 0 | 0 | 96.9 | 0.41 | 2347 | 0 | 103 | 0 | 4.7 | 104 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 44.1 |
| 13 | 83 | 115 | 0 | 0 | 96. | 0.4 | 235 | 0 | 10 | 0 | 7.1 | 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 36. |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5 | 3 | 0 | | | 9 | 1 | 8 | | 3 | | | 4 | | | | | | | | | 9 |
| 135 | 833 | 1035 | 0 | 0 | 96.9 | 0.41 | 2281 | 0 | 103 | 0 | 0 | 104 | 115 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 25.3 |
| 135 | 833 | 1035 | 0 | 0 | 96.9 | 0.41 | 2316 | 0 | 103 | 0 | 2.4 | 104 | 115 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 41.9 |
| 135 | 833 | 1035 | 0 | 0 | 96.9 | 0.41 | 2298 | 0 | 103 | 0 | 4.7 | 104 | 115 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 29.7 |
| 135 | 833 | 1035 | 0 | 0 | 96.9 | 0.41 | 2315 | 0 | 103 | 0 | 7.1 | 104 | 115 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 19.3 |
| 135 | 833 | 920 | 0 | 0 | 96.9 | 0.41 | 2226 | 0 | 103 | 0 | 0 | 104 | 230 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 22.9 |
| 135 | 833 | 920 | 0 | 0 | 96.9 | 0.41 | 2226 | 0 | 103 | 0 | 2.4 | 104 | 230 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 32.3 |
| 135 | 833 | 920 | 0 | 0 | 96.9 | 0.41 | 2190 | 0 | 103 | 0 | 4.7 | 104 | 230 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 26.9 |
| 135 | 833 | 920 | 0 | 0 | 96.9 | 0.41 | 2209 | 0 | 103 | 0 | 7.1 | 104 | 230 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 19.3 |
| 135 | 833 | 805 | 0 | 0 | 96.9 | 0.41 | 2171 | 0 | 103 | 0 | 0 | 104 | 345 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 19.7 |
| 135 | 833 | 805 | 0 | 0 | 96.9 | 0.41 | 2178 | 0 | 103 | 0 | 2.4 | 104 | 345 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 23.7 |
| 135 | 833 | 805 | 0 | 0 | 96.9 | 0.41 | 2171 | 0 | 103 | 0 | 4.7 | 104 | 345 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 22.3 |
| 135 | 833 | 805 | 0 | 0 | 96.9 | 0.41 | 2190 | 0 | 103 | 0 | 7.1 | 104 | 345 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 19.7 |
| 26 | 83 | 114 | 0 | 0 | 98. | 0.3 | 237 | 0 | 0 | 0 | 0 | 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 41. |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 9 | 2 | 8 | | | 2 | 7 | 2 | | | | | 4 | | | | | | | | | 8 |
| 269 | 832 | 1148 | 0 | 0 | 98.2 | 0.37 | 2398 | 0 | 0 | 0 | 2.69 | 104 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 58 |
| 269 | 832 | 1148 | 0 | 0 | 98.2 | 0.37 | 2389 | 0 | 0 | 0 | 5.37 | 104 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 43.2 |
| 269 | 832 | 1148 | 0 | 0 | 98.2 | 0.37 | 2359 | 0 | 0 | 0 | 8.06 | 104 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 37.6 |
| 269 | 832 | 1033 | 0 | 0 | 98.2 | 0.37 | 2313 | 0 | 0 | 0 | 0 | 104 | 115 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 46.7 |
| 269 | 832 | 1033 | 0 | 0 | 98.2 | 0.37 | 2326 | 0 | 0 | 0 | 2.69 | 104 | 115 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 53.9 |
| 269 | 832 | 1033 | 0 | 0 | 98.2 | 0.37 | 2317 | 0 | 0 | 0 | 5.37 | 104 | 115 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 46.1 |
| 269 | 832 | 1033 | 0 | 0 | 98.2 | 0.37 | 2308 | 0 | 0 | 0 | 8.06 | 104 | 115 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 39.8 |
| 269 | 832 | 918 | 0 | 0 | 98.2 | 0.37 | 2235 | 0 | 0 | 0 | 0 | 104 | 230 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 26.9 |
| 269 | 832 | 918 | 0 | 0 | 98.2 | 0.37 | 2259 | 0 | 0 | 0 | 2.69 | 104 | 230 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 36.3 |
| 269 | 832 | 918 | 0 | 0 | 98.2 | 0.37 | 2272 | 0 | 0 | 0 | 5.37 | 104 | 230 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 32.1 |
| 269 | 832 | 918 | 0 | 0 | 98.2 | 0.37 | 2263 | 0 | 0 | 0 | 8.06 | 104 | 230 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 27.7 |
| 269 | 832 | 804 | 0 | 0 | 98.2 | 0.37 | 2196 | 0 | 0 | 0 | 0 | 104 | 345 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 25.7 |
| 26 | 83 | 804 | 0 | 0 | 98. | 0.3 | 219 | 0 | 0 | 0 | 2.6 | 10 | 34 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 33 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 9 | 2 | | | | 2 | 7 | 9 | | | | 9 | 4 | 5 | | | | | | | | |
| 269 | 832 | 804 | 0 | 0 | 98.2 | 0.37 | 2184 | 0 | 0 | 0 | 5.37 | 104 | 345 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 23.8 |
| 269 | 832 | 804 | 0 | 0 | 98.2 | 0.37 | 2165 | 0 | 0 | 0 | 8.06 | 104 | 345 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 19.9 |
| 269 | 832 | 1148 | 0 | 0 | 98.2 | 0.37 | 2372 | 0 | 0 | 0 | 0 | 104 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 47.6 |
| 269 | 832 | 1148 | 0 | 0 | 98.2 | 0.37 | 2398 | 0 | 0 | 0 | 2.69 | 104 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 63.5 |
| 269 | 832 | 1148 | 0 | 0 | 98.2 | 0.37 | 2389 | 0 | 0 | 0 | 5.37 | 104 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 50.7 |
| 269 | 832 | 1148 | 0 | 0 | 98.2 | 0.37 | 2359 | 0 | 0 | 0 | 8.06 | 104 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 41.3 |
| 269 | 832 | 1033 | 0 | 0 | 98.2 | 0.37 | 2313 | 0 | 0 | 0 | 0 | 104 | 115 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 49.2 |
| 269 | 832 | 1033 | 0 | 0 | 98.2 | 0.37 | 2326 | 0 | 0 | 0 | 2.69 | 104 | 115 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 61.5 |
| 269 | 832 | 1033 | 0 | 0 | 98.2 | 0.37 | 2317 | 0 | 0 | 0 | 5.37 | 104 | 115 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 53.6 |
| 269 | 832 | 1033 | 0 | 0 | 98.2 | 0.37 | 2308 | 0 | 0 | 0 | 8.06 | 104 | 115 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 42.1 |
| 269 | 832 | 918 | 0 | 0 | 98.2 | 0.37 | 2235 | 0 | 0 | 0 | 0 | 104 | 230 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 36.7 |
| 269 | 832 | 918 | 0 | 0 | 98.2 | 0.37 | 2259 | 0 | 0 | 0 | 2.69 | 104 | 230 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 41.6 |
| 26 | 83 | 918 | 0 | 0 | 98. | 0.3 | 227 | 0 | 0 | 0 | 5.3 | 10 | 23 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 34. |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 9 | 2 | | | | 2 | 7 | 2 | | | | 7 | 4 | 0 | | | | | | | | 8 |
| 269 | 832 | 918 | 0 | 0 | 98.2 | 0.37 | 2263 | 0 | 0 | 0 | 8.06 | 104 | 230 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 42.3 |
| 269 | 832 | 804 | 0 | 0 | 98.2 | 0.37 | 2196 | 0 | 0 | 0 | 0 | 104 | 345 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 34.8 |
| 269 | 832 | 804 | 0 | 0 | 98.2 | 0.37 | 2199 | 0 | 0 | 0 | 2.69 | 104 | 345 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 38.4 |
| 269 | 832 | 804 | 0 | 0 | 98.2 | 0.37 | 2184 | 0 | 0 | 0 | 5.37 | 104 | 345 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 28.6 |
| 269 | 832 | 804 | 0 | 0 | 98.2 | 0.37 | 2165 | 0 | 0 | 0 | 8.06 | 104 | 345 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 24.4 |
| 440 | 988 | 692 | 0 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0.8 | 0 | 0 | 5 | 16.7 |
| 440 | 988 | 692 | 0 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0.8 | 0 | 0 | 7 | 19.1 |
| 440 | 988 | 692 | 0 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0.8 | 0 | 0 | 28 | 30.3 |
| 440 | 988 | 692 | 0 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0.8 | 0 | 0 | 56 | 36.5 |
| 440 | 988 | 692 | 0 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0.8 | 0 | 0 | 5 | 17.7 |
| 440 | 988 | 692 | 0 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0.8 | 0 | 0 | 7 | 20.1 |
| 440 | 988 | 692 | 0 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0.8 | 0 | 0 | 28 | 31.8 |
| 44 | 98 | 692 | 0 | 0 | 17 | 0.4 | 229 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0. | 0 | 0 | 56 | 38. |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 8 | | | | 6 | | 6 | | | | | | | | | | 8 | | | | 1 |
| 440 | 494 | 692 | 494 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0.8 | 0 | 0 | 5 | 15.4 |
| 440 | 494 | 692 | 494 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0.8 | 0 | 0 | 7 | 18.1 |
| 440 | 494 | 692 | 494 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0.8 | 0 | 0 | 28 | 27.5 |
| 440 | 494 | 692 | 494 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0.8 | 0 | 0 | 56 | 32.5 |
| 440 | 0 | 692 | 988 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0.8 | 0 | 0 | 5 | 14 |
| 440 | 0 | 692 | 988 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0.8 | 0 | 0 | 7 | 16.1 |
| 440 | 0 | 692 | 988 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0.8 | 0 | 0 | 28 | 26 |
| 440 | 0 | 692 | 988 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0.8 | 0 | 0 | 56 | 29.9 |
| 440 | 494 | 692 | 494 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0.8 | 0 | 0 | 5 | 15.7 |
| 440 | 494 | 692 | 494 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0.8 | 0 | 0 | 7 | 18.1 |
| 440 | 494 | 692 | 494 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0.8 | 0 | 0 | 28 | 28.8 |
| 440 | 494 | 692 | 494 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0.8 | 0 | 0 | 56 | 33.9 |
| 44 | 0 | 692 | 98 | 0 | 17 | 0.4 | 229 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0. | 0 | 0 | 5 | 14. |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | | | 8 | | 6 | | 6 | | | | | | | | | | 8 | | | | 4 |
| 440 | 0 | 692 | 988 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0.8 | 0 | 0 | 7 | 17.1 |
| 440 | 0 | 692 | 988 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0.8 | 0 | 0 | 28 | 27.2 |
| 440 | 0 | 692 | 988 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0.8 | 0 | 0 | 56 | 32 |
| 440 | 988 | 692 | 0 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 5 | 13 |
| 440 | 988 | 692 | 0 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 7 | 15.1 |
| 440 | 988 | 692 | 0 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 28 | 23.7 |
| 440 | 988 | 692 | 0 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 56 | 28.1 |
| 440 | 988 | 692 | 0 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0 | 0 | 0 | 5 | 13.9 |
| 440 | 988 | 692 | 0 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0 | 0 | 0 | 7 | 15.9 |
| 440 | 988 | 692 | 0 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0 | 0 | 0 | 28 | 25.8 |
| 440 | 988 | 692 | 0 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0 | 0 | 0 | 56 | 28.9 |
| 440 | 494 | 692 | 494 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 5 | 11.1 |
| 44 | 49 | 692 | 49 | 0 | 24 | 0.5 | 236 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 7 | 13. |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 4 | | 4 | | 2 | 5 | 2 | | | | | | | | | | | | | 7 |
| 440 | 494 | 692 | 494 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 28 | 21.1 |
| 440 | 494 | 692 | 494 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 56 | 25.3 |
| 440 | 0 | 692 | 988 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0 | 0 | 0 | 5 | 10.7 |
| 440 | 0 | 692 | 988 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0 | 0 | 0 | 7 | 12.4 |
| 440 | 0 | 692 | 988 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0 | 0 | 0 | 28 | 20.6 |
| 440 | 0 | 692 | 988 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0 | 0 | 0 | 56 | 23.7 |
| 440 | 494 | 692 | 494 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0 | 0 | 0 | 5 | 12.4 |
| 440 | 494 | 692 | 494 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0 | 0 | 0 | 7 | 13.9 |
| 440 | 494 | 692 | 494 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0 | 0 | 0 | 28 | 21.7 |
| 440 | 494 | 692 | 494 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0 | 0 | 0 | 56 | 26.8 |
| 440 | 0 | 692 | 988 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0 | 0 | 0 | 5 | 11.2 |
| 440 | 0 | 692 | 988 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0 | 0 | 0 | 7 | 13.1 |
| 44 | 0 | 692 | 98 | 0 | 24 | 0.5 | 236 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0 | 0 | 0 | 28 | 21. |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | | | 8 | | 2 | 5 | 2 | | | | | | | | | | | | | | 4 |
| 440 | 0 | 692 | 988 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 1 | 0 | 0 | 0 | 56 | 24.8 |
| 440 | 988 | 692 | 0 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.8 | 0 | 0 | 5 | 19 |
| 440 | 988 | 692 | 0 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.8 | 0 | 0 | 7 | 22 |
| 440 | 988 | 692 | 0 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.8 | 0 | 0 | 28 | 34.6 |
| 440 | 988 | 692 | 0 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.8 | 0 | 0 | 56 | 26.1 |
| 440 | 988 | 692 | 0 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0.8 | 0 | 0 | 5 | 20 |
| 440 | 988 | 692 | 0 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0.8 | 0 | 0 | 7 | 23.1 |
| 440 | 988 | 692 | 0 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0.8 | 0 | 0 | 28 | 36.2 |
| 440 | 988 | 692 | 0 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0.8 | 0 | 0 | 56 | 41.5 |
| 440 | 494 | 692 | 494 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.8 | 0 | 0 | 5 | 16.9 |
| 440 | 494 | 692 | 494 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.8 | 0 | 0 | 7 | 19.6 |
| 440 | 494 | 692 | 494 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.8 | 0 | 0 | 28 | 31 |
| 44 | 49 | 692 | 49 | 0 | 17 | 0.4 | 229 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0. | 0 | 0 | 56 | 37. |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 4 | | 4 | | 6 | | 6 | | | | | | | | | | 8 | | | | 2 |
| 440 | 0 | 692 | 988 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0.8 | 0 | 0 | 5 | 15.9 |
| 440 | 0 | 692 | 988 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0.8 | 0 | 0 | 7 | 18.4 |
| 440 | 0 | 692 | 988 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0.8 | 0 | 0 | 28 | 29.7 |
| 440 | 0 | 692 | 988 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0.8 | 0 | 0 | 56 | 34.7 |
| 440 | 494 | 692 | 494 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0.8 | 0 | 0 | 5 | 18.1 |
| 440 | 494 | 692 | 494 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0.8 | 0 | 0 | 7 | 20.6 |
| 440 | 494 | 692 | 494 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0.8 | 0 | 0 | 28 | 32.6 |
| 440 | 494 | 692 | 494 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0.8 | 0 | 0 | 56 | 39.3 |
| 440 | 0 | 692 | 988 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0.8 | 0 | 0 | 5 | 16.7 |
| 440 | 0 | 692 | 988 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0.8 | 0 | 0 | 7 | 19.5 |
| 440 | 0 | 692 | 988 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0.8 | 0 | 0 | 28 | 31 |
| 440 | 0 | 692 | 988 | 0 | 176 | 0.4 | 2296 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0.8 | 0 | 0 | 56 | 35.8 |
| 44 | 98 | 692 | 0 | 0 | 24 | 0.5 | 236 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5 | 14. |

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 8 | | | | 2 | 5 | 2 | | | | | | | | | | | | | | 8 |
| 440 | 988 | 692 | 0 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 17 |
| 440 | 988 | 692 | 0 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 26.6 |
| 440 | 988 | 692 | 0 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 56 | 32 |
| 440 | 988 | 692 | 0 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 | 5 | 15.8 |
| 440 | 988 | 692 | 0 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 | 7 | 17.8 |
| 440 | 988 | 692 | 0 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 | 28 | 27.3 |
| 440 | 988 | 692 | 0 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 | 56 | 33.7 |
| 440 | 494 | 692 | 494 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5 | 13.5 |
| 440 | 494 | 692 | 494 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 28.8 |
| 440 | 494 | 692 | 494 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 15.4 |
| 440 | 494 | 692 | 494 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 56 | 24.2 |
| 440 | 0 | 692 | 988 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 | 5 | 12.5 |
| 44 | 0 | 692 | 98 | 0 | 24 | 0.5 | 236 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 | 7 | 14. |

| | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | | | 8 | | 2 | 5 | 2 | | | | | | | | | | | | | 2 |
| 440 | 0 | 692 | 988 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 | 28 | 23.6 |
| 440 | 0 | 692 | 988 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 | 56 | 27.2 |
| 440 | 494 | 692 | 494 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 | 5 | 13.8 |
| 440 | 494 | 692 | 494 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 | 7 | 16.1 |
| 440 | 494 | 692 | 494 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 | 28 | 25 |
| 440 | 494 | 692 | 494 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 | 56 | 30.9 |
| 440 | 0 | 692 | 988 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 | 5 | 12.7 |
| 440 | 0 | 692 | 988 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 | 7 | 15.4 |
| 440 | 0 | 692 | 988 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 | 28 | 24.1 |
| 440 | 0 | 692 | 988 | 0 | 242 | 0.55 | 2362 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0 | 56 | 27.7 |